ESSAYS ON THE

RURAL OPIOID

CRISIS

By

DEVON P. MEADOWCROFT

Bachelor of Science in Animal Science
University of Vermont
Burlington, Vermont
2013

Master of Science in Agricultural and Resource
Economics
University of Delaware
Newark, Delaware
2016

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
May, 2019

ESSAYS ON THE

RURAL OPIOID

CRISIS

Dissertation Approved:

Dr. Brian E. Whitacre

Dissertation Adviser

Dr. B. Wade Brorsen

Dr. David W. Shideler

Dr. Denna Wheeler

Dr. Chad A. Malone

ACKNOWLEDGEMENTS

Thank you to my committee members, and advisor Dr. Whitacre for their guidance and input throughout this process.

Name: DEVON P. MEADOWCROFT

Date of Degree: MAY, 2019

Title of Study: ESSAYS ON THE RURAL OPIOID CRISIS

Major Field: AGRICULTURAL ECONOMICS

Abstract: Rural areas in the U.S. have been notably affected by the opioid crisis, resulting in higher rates of opioid-related deaths and misuse than their urban counterparts. This dissertation assesses the effectiveness of existing strategies aimed at reducing opioid misuse, and also describes an Extension-led effort to engage rural communities struggling with this issue. The first study focuses on opioid treatment programs (OTPs) in the South census region. Through coarsened exact matching (CEM), the study determines if OTP presence is associated with reductions in the opioid-related death rate in counties nearby the OTP. Rural and urban counties are analyzed separately, to see if the results vary for these different types of areas. The findings of this study suggest that OTPs are not negatively associated with future opioid-related deaths, in either rural or urban counties. The second study examines prescription drug monitoring programs (PDMPs), which are statewide online programs that monitor controlled substance prescriptions. Multiple correspondence analysis is used to create a measure of a state's PDMP robustness. The aim of this study is to evaluate if states with more stringent PDMPs in place are associated with increased incidences of illicit opioid deaths, due to prescription opioids being more difficult to obtain in these areas. Results show that continuous measures of PDMP strength are not generally associated with the prescription opioid- or heroin-related death rate. Yet, one model does confirm the hypothesis that stricter PDMPs are related to more illicit opioid use. When the PDMP scores are broken into quartiles in the models, only the lowest quartile of scores (i.e. least stringent) is seen to have a negative association with overdose deaths. For the third study, a series of three community meetings were held in Ardmore, Oklahoma. Community stakeholders attended these meetings, and a variety of data collection techniques assessed where they would like to direct future resources aimed at reducing opioid misuse in their area. The participants noted that they would like funding to go towards increasing access to opioid treatment options, and to youth education programs in their community.

TABLE OF CONTENTS

Chapter Page

LIST OF TABLES

Table Page

LIST OF FIGURES

CHAPTER I

INTRODUCTION

The opioid crisis has gathered widespread attention in the U.S. in recent years, with policy-makers, medical professionals, and community members continually looking at ways to effectively address the issue. The rural U.S. has particularly struggled with high rates of opioid-related deaths, which is compounded by the lack of available treatment options in these areas (Rosenblatt et al., 2015; Hirchak and Murphy, 2017; Mack, 2017). Therefore, it is not surprising that when surveyed, about half of rural residents state that they know someone who has had an opioid addiction (Robert Wood Johnson Foundation, 2018). The goal of this dissertation is to provide evidence of "what works" in preventing and treating opioid misuse in rural areas. This dissertation is comprised of three studies, which examine the opioid crisis at the national, regional, and community level.

The first study in Chapter 2 determines whether opioid treatment programs (OTPs) present in the South census regional have any association with the opioid-related death rate at the county-level. OTPs provide medication-assisted treatment, which combines mediations and behavioral therapies into a patient's treatment plan. Medication-assisted treatment has been proven to be a highly effective form of treatment for someone with opioid misuse issues (Schwartz et al., 2013; Zaller et al., 2013; Volkow et al. 2014). Therefore, some advocates have called for more rural OTPs, but their impact on death rates has not been formally explored in the existing literature. A matching technique called coarsened exact matching (CEM) is used in this study. The objective of CEM is to "match" counties in the South with and without access to an OTP before 2013 based on similarities in opioid-related death rates from 2011 through, opioid prescription rates, and demographic characteristics. An important feature of this study is that metropolitan and non-metropolitan counties are analyzed separately during the CEM and estimation process, to see if the relationship between OTPs and opioid-related deaths differs between these types of counties.

Chapter 3 is comprised of the second study, which is an examination of prescription drug monitoring programs (PDMPs). PDMPs are statewide electronic databases that store information on prescriptions for controlled substances, with data being submitted by pharmacists. Each state has autonomy in controlling how their PDMP is operated. Currently, every U.S. state including D.C. has a PDMP, with the exception of Missouri. This study explores whether having a strict PDMP with more regulations in place has the unintended consequence of increasing the rate of illicit opioid deaths. The hypothesis is that stringent PDMPs make prescription opioids more difficult to access, so misusers switch to illicit opioids, such as heroin. For this study, a statistical method called multiple correspondence analysis (MCA) is used to create the measure of PDMP strength. For the MCA, eleven PDMP regulations are combined into a single score based on the correlations between the regulations. Then, two-way fixed effects models are run on a panel dataset which covers the years 1999 to 2016. Outcome variables include a state's illicit- or prescription opioid-related death rate. Independent variables include the score of PDMP strength, state demographic variables, the agency in charge of operating the state PDMP, and other variables thought to have an impact on the opioid-related death rates.

The final study in Chapter 4 revolves around a series of three community meetings that were held in the rural town of Ardmore, Oklahoma. Ardmore has historically struggled with opioid misuse, and during these meetings community stakeholders learned about and discussed programs they can utilize that relate to opioids. Four categories of programs were presented in the meetings, (A) programs that try to reduce opioid supply, (B) program that try to reduce opioid demand, (C) opioid treatment programs, and (D) overdose prevention and recovery programs. To inform the participants about the four categories of programs, experts in each of the areas presented on the programs' features and on current work in these fields. The aim of the meetings was for participants to determine a ranking of the four categories of programs, based on the needs of the Ardmore area. Data collection occurred through pre/post surveys, study circles, and a participant voting exercise. The surveys asked participants their perceptions on opioid-related issues, along with their familiarity and beliefs on the different programs discussed during the meetings. Surveys were distributed at the beginning of the first and end of the third meetings, to evaluate if participant perceptions changed throughout the course of the study. In the study circles, participants were randomly divided into small groups and asked questions related to the opioid crisis in Ardmore, and on the programs presented, to prompt conversation. The participant voting exercise occurred at the third meeting. Here, participants had to allocate a hypothetical set of funds to each of the four programs. Thus, the results from the exercise serve as a representation of where the stakeholders would like to devote future funds as they try to reduce the effects of opioid misuse in Ardmore.

Each study discussed above is included with a more thorough explanation of the motivation and methodology, along with the study's results in Chapters 2 through 4. Conclusions and subsequent policy implications are also explored in detail. The dissertation ends with a general overview of the studies' outcomes, which is laid out in Chapter 5.

CHAPTER II

DO RURAL OPIOID TREATMENT PROGRAM (OTP) FACILITIES REDUCE DEATHS?

In recent years, America has been greatly impacted by the opioid epidemic. The number of deaths caused by opioids has been steadily rising since the start of the twenty-first century, and in October 2017 the opioid epidemic was classified as a national public health emergency by the Department of Health and Human Services. Even though the opioid epidemic has been widespread across the U.S., rural America has been particularly affected. The Centers for Disease Control and Prevention (CDC) estimates that the drug overdose death rate is higher in rural areas in comparison to urban ones, and a majority of rural residents (57%) agree that opioid addiction is a serious problem in their community (Mack et al., 2017; Robert Wood Johnson Foundation, 2018).

One particular issues with combatting the opioid epidemic in the rural U.S. is the lack of access to treatment centers. Urban areas are more likely to have opioid treatment centers and doctors who are licensed to prescribe medications to help alleviate opioid addictions (Kvamme et al., 2013; Rosenblatt et al., 2015; Stein et al., 2015; Hirchak and Murphy, 2017). While previous studies have identified the extent to which rural geographies lack opioid treatment options, there is a dearth of evidence on the effectiveness of treatment centers that do exist. Given that other approaches to dealing with the opioid crisis are also available, empirical assessment is crucial in assessing whether substance use treatment centers are a worthwhile investment for rural policymakers.

The opioid treatment option of interest in this study is medication-assisted treatment (MAT), which is the CDC and Substance Abuse and Mental Health Services Administration (SAMHSA) recommended plan. MAT has proven to be a successful form of treatment in curbing opioid misuse (Schwartz et al., 2013; Zaller et al., 2013; Volkow et al. 2014). and incorporates prescribed medications in addition to behavioral counseling into a patient's treatment plan. The goal of the medications used[1] in a MAT program is to curb the symptoms from opioid withdrawal and to prevent relapse (Connery, 2015).This form of treatment differs from abstinence-based programs, which do not integrate prescription medicine into a patient's treatment plan. MAT is an indefinite process, and patients can potentially be on these medications for the rest of their lives (Center for Substance Abuse Treatment, 2005; Fullerton et al., 2014). The treatment centers that utilize MAT are referred to as opioid treatment programs (OTPs), which are certified and accredited by SAMHSA. OTPs can be present in outpatient, residential, or hospital settings and the medication provided to patients (methadone, buprenorphine, or naltrexone) depends on the program and the patient's individual treatment plan (Center for Substance Abuse Treatment, 2005). It is important to note that OTPs are a different treatment option than being prescribed buprenorphine through a medical professional. The number of patients receiving treatment through a buprenorphine-waivered physician has increased in recent years due to its ease and accessibility (Dick et al., 2014; Stein et al., 2015), however this study only focuses on OTPs and their effectiveness in curbing misuse.

[1] Currently, the Food and Drug Administration (FDA) approves three drugs for use in MAT: buprenorphine, methadone, and naltrexone (Food and Drug Administration, 2018).

This study examines counties in the South census region, which had the highest number of drug overdose deaths out of all census regions in 2016 (Centers for Disease Control and Prevention, 2018a). It uses coarsened exact matching (CEM) to uncover how OTPs are associated with opioid death rates. CEM creates 'mirrored counterparts' to counties with OTP access by matching them to non-treated counties with similar characteristics, including 2011-2013 opioid death rates. Two treatments are examined, one being if a county had an OTP as of 2013, and the other being if a neighboring county contained an OTP in 2013. After reducing the sample via CEM, opioid death rates in the following three years (2014-2016) are compared across treatment and control groups using regression analysis. Metro and non-metro counties are analyzed separately due to differences in accessibility to treatment centers, opioid death rates, and underlying social structures. Thus, we seek to determine if the association between OTPs and opioid-related deaths varies between metropolitan and non-metropolitan counties, and to what extent a disparity exists.

Barriers to Treatment in Rural Areas

Even though MAT programs have been shown to be highly successful in terms of ending opioid misuse, a gap exists between the availability of these programs and the amount of patients who need treatment (Jones et al., 2015). The shortage of MAT programs in the U.S. is more evident in rural areas in comparison to urban ones. Research has found that rural health centers have about half the odds of urban centers in offering MAT programs with buprenorphine dispensed on site (Jones, 2018). Further, the number of physicians who have waivers to prescribe buprenorphine (a medication used in MAT) is significantly higher in urban areas, even after adjusting to a per-capita basis (Stein et al., 2015). It is worth reiterating, however, that medical professionals prescribing buprenorphine are not considered OTPs.

Previous studies have found that increased distance to health care services is problematic for rural health outcomes (Skinner and Slifkin, 2007; Huang et al., 2009; Stephens et al., 2013). Similarly, transportation to and from OTPs is also an issue for rural patients (Rosenblum et al., 2011). During focus group interviews conducted in the rural South, both clients and stakeholders of substance use treatment centers identified issues with transportation as an obstacle to attending treatment services (Browne et al., 2016). These concerns were echoed in focus groups done in rural Kentucky with pregnant women undergoing substance use treatment (Jackson and Shannon, 2012). These issues are further compounded in rural areas by MAT being a long-term treatment plan[2], with patients needing to visit the OTP daily (if they are receiving methadone), at least weekly (if they are receiving buprenorphine), or daily or thrice weekly (if they are receiving naltrexone) until they have progressed to a certain point in their treatment (Center for Substance Abuse Treatment, 2004; Center for Substance Abuse Treatment, 2005; Kampman and Jarvis, 2015).

An additional barrier to attending and successfully completing treatment in rural locations is the heightened stigma that patients and physicians face. During focus groups carried out in the rural South, clients detailed how the close-knit culture of rural areas leads to a lack of anonymity when getting treatment in those communities (Browne et al., 2016; Rigg et al., 2018). Under these circumstances, an OTP location in a neighboring county (where staying anonymous is more likely) might be preferred. However, stigma is not limited to just rural patients. Surveys and interviews of rural physicians have shown that stigma is a deterrent for doctors exploring the possibility of prescribing buprenorphine or similar opioid-dependence medications to patients (Andrilla et al., 2017; Andrilla et al., 2019).

Does More Access to Treatment Increase Success?

[2] The National Institute on Drug Abuse suggests that methadone, a prescription medication used in certain MAT programs, should be given to patients for a minimum of 12 months in order to prevent relapse (National Institute on Drug Abuse, 2018). Patients are able to take home doses of medication at a certain point during their treatment.

Studies on the relationship between proximity to substance use treatment and drug misuse have shown mixed results. Notably, most of this research has taken place in large metropolitan areas. In a study of Baltimore patients, those who had to travel less than a mile for their drug treatment services were more likely to complete treatment than those who had to travel further (Beardsley et al., 2003). Distance between a patient's residence and their OTP was found to be positively associated with the amount of missed methadone doses in the first month of treatment for patients in Spokane County in Washington state (Amiri et al., 2018). Similarly, researchers found that an increase in transportation distance for rural patients was associated with higher rates of relapse and incarceration following treatment (Oser and Harp, 2015).

In contrast, other studies have found that the closer treatment is to a patient's residence, the more likely they are to forgo sobriety in the future. A survey of heroin users in Houston who lived in close proximity to treatment facilities (and in areas with a multitude of facilities) reported that they were more likely to purchase and use heroin in the future in comparison to those who did not live close to many treatment centers (Kao et al., 2014). In Philadelphia, patients who had received inpatient substance use treatment who lived nearby more than six narcotics anonymous (NA) and/or alcoholics anonymous (AA) meeting location sites were found to have a lower probability of attending outpatient treatment (Stahler et al., 2007). Researchers attributed this counterintuitive finding - that heroin use increased with proximity to treatment - to the fact that a majority of OTPs are located in urban neighborhoods, where illicit substances are easily obtainable (Rosenblum et al., 2011). One study saw a similar result with the neighborhoods where substance use treatment centers in Los Angeles County are located, which were economically disadvantaged areas (Jacobson, 2006). Therefore, the neighborhoods where treatment centers are located could promote relapse (with high rates of use in surrounding locations) and subsequent drug use. However, no studies we are aware of studied this issue in a rural environment.

Materials and Methods

Sample

All data for this study is aggregated at the county-level for states in the South census region, which is comprised of sixteen states plus the District of Columbia[3]. Information regarding opioid related deaths is gathered through the National Vital Statistics System (NVSS) multiple cause of death mortality files, and is accessed through the CDC Wonder database. Following CDC practices, opioid deaths are considered to be any death corresponding to the International Classification of Disease, Tenth Revision multiple cause-of-death codes T40.0, T40.1, T40.2, T40.3, and T40.4[4]. Age-adjusted death rates per 100,000 residents are generated from the county-level death counts[5]. One challenge in working with this data is overcoming suppression. For privacy reasons, the CDC suppresses any county-level death count if it less than 9. To overcome this issue, multiple years of age-adjusted death rates are aggregated in two groups (2011-2013 and 2014-2016). When multiple years of data are compiled, death counts are aggregated and there are more counties with data that is not suppressed – therefore decreasing the amount of missing information in the sample. Even so, data suppression still affects a high number of our counties of interest. Of the 1,423 counties in the South, 488 (34%) and 553 (39%) counties have non-suppressed age adjusted death rates for 2011-2013 and 2014-2016, respectively. 442 counties (31%) have data in both time periods, allowing percentage change to be calculated. As might be expected, the data suppression issue is worse for non-metropolitan counties.

---

[3] The states included in the South census region are: Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia.

[4] The codes represent the following drug-related deaths, T40.0: opium, T40.1: heroin, T40.2: other opioids, T40.3: methadone, T40.4: other synthetic narcotics.

[5] Age-adjusted death rates account for the counties' differences in age distributions, so that the counties in the sample can be compared to one another (Anderson and Rosenberg, 1988). When death rates are age adjusted, the CDC provides age adjusted death rates for counties with death counts greater than 20. Age adjusted death rates were calculated manually for counties with 10 to 20 deaths using the average change (from crude death rate to age adjusted rate) for counties with a similar population size that do have CDC-provided age-adjusted death rates. The final age-adjusted death rates are compared to CDC values (Centers for Disease Control and Prevention, 2018) to verify calculation accuracy.

The publicly available National Directory of Drug and Alcohol Treatment facilities is used to find the locations of OTPs, and to determine what year they started their services. As of 2017, 415 OTPs are in the South. 314 of those were open in 2013, which are the ones of interest in this study. Figure 2.1 shows where these OTPs are located, and distinguishes between metropolitan and non-metropolitan counties. 286 of the 314 OTPs (91%) are located in metropolitan counties, with the remaining 28 being in non-metropolitan counties, clearly demonstrating their urban bias.

To control for county-level opioid supply in our analysis, data is pulled from the CDC's U.S. Opioid Prescribing Rate Maps (Centers for Disease Control and Prevention, 2018b). The CDC provides data on the amount of opioid prescriptions per 100 people in a county. An opioid prescription is considered to be either an initial or refill prescription which is dispensed at a retail pharmacy. To stay consistent with the rest of our data, county-level prescription rates are averaged between 2011 and 2013.

Lastly, the 2009-2013 American Community Survey (ACS) was used to collect county-level demographic information such as population, percentage of the population who is white, and poverty rates. Supplemental information is pulled from the USDA Economic Research Service (ERS). 830 (58%) of the counties in the South are non-metropolitan based on ERS rural-urban continuum codes.

Coarsened Exact Matching (CEM)

A Brief Overview of Coarsened Exact Matching (CEM)

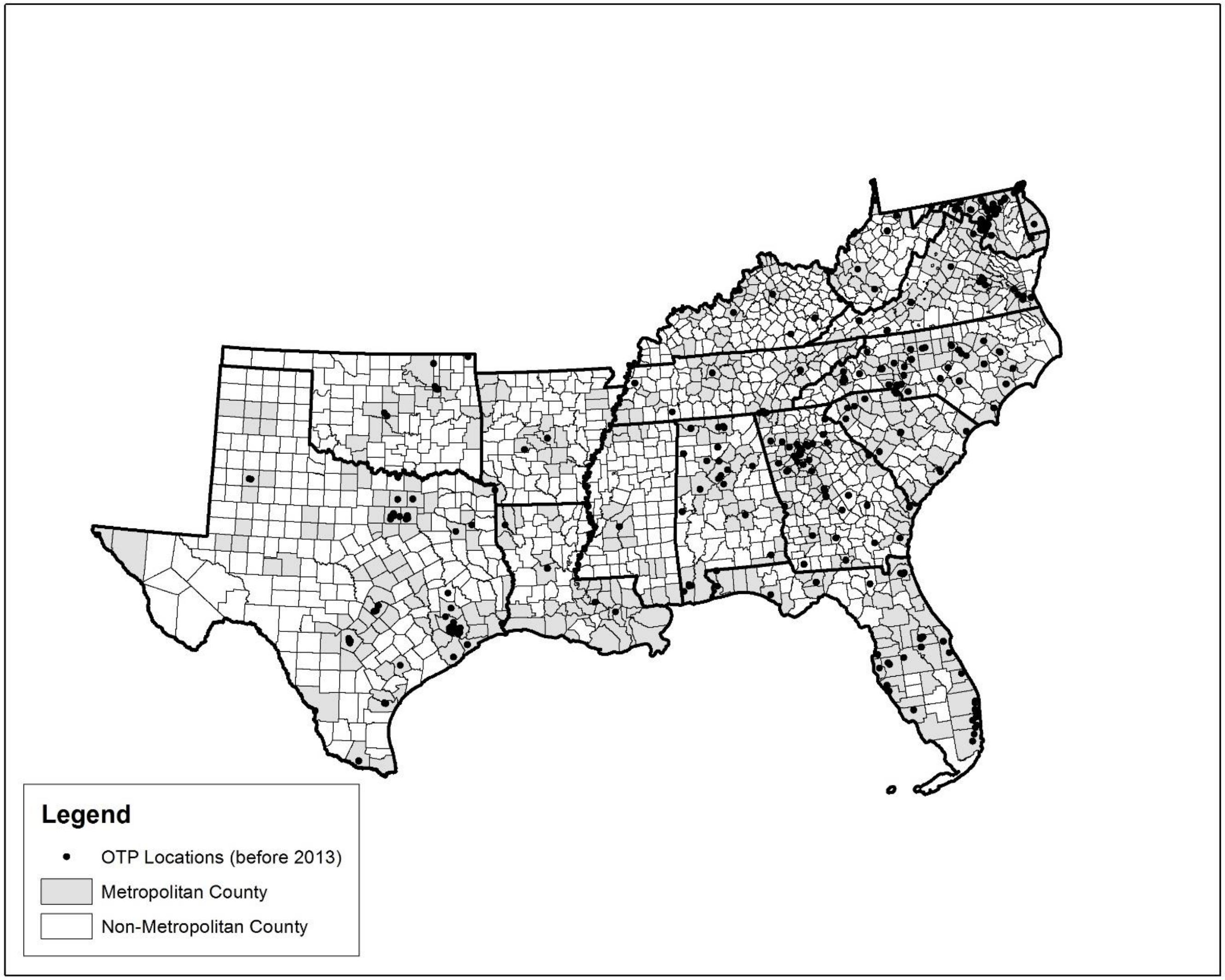


Figure 2.1. OTPs in South Census Region Prior to 2013

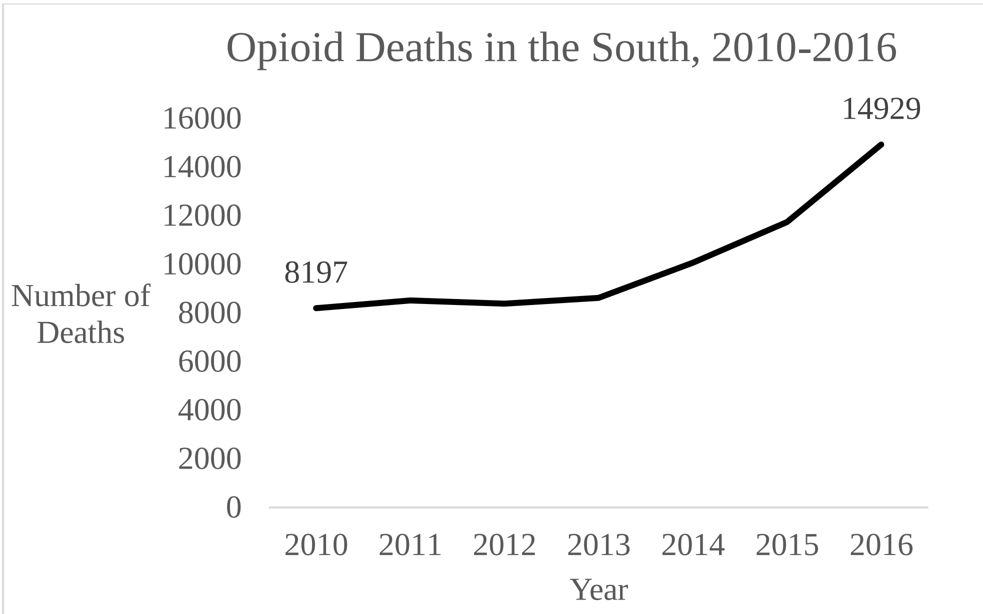


Figure 2.2. Opioid Related Deaths in the South Census Region (2010-2016)

Table 2.1. Descriptive Statistics for Non-Metropolitan and Metropolitan Counties

	Treatment 1: OTP in County before 2013						Treatment 2: OTP in Neighboring before 2013					
	Non-Metropolitan Counties			Metropolitan Counties			Non-Metropolitan Counties			Metropolitan Counties		
	Treated	Control	Ttest	Treated	Control	Ttest	Treated	Control	Ttest	Treated	Control	Ttest
Death Rates												
Age Adjusted Death Rate (2011-2013) per 100,000 residents	19.23	20.85		9.02	11.08	**	21.35	20.18		10.31	9.98	
Age Adjusted Death Rate (2014-2016) per 100,000 residents	20.44	19.89		13.56	14.28		29.59	19.36		13.78	14.47	
Percentage change between 2014-2016 and 2011-2013 Death Rates[a]	20.35	15.81		62.76	44.98	**	22.17	11.13		52.83	52.63	
Covariates (2009-2013)												
Prescription rate	171.05	96.86	***	103.24	90.85	**	106.09	95.86	**	91.21	99.52	*
Population	42,654.04	18,560.38	***	410,806.30	73,536.87	***	30,777.05	20,358.42	***	182,061.10	125,342.10	**
Percent white	76.17	69.60		61.68	73.38	***	68.96	70.24		69.29	72.21	*
Poverty rate	22.60	21.66		16.34	16.47		22.02	21.53		15.83	17.56	***
Number of Counties	27	803		156	437		278	552		386	207	
Number with Age Adjusted Death Rates (2011-2013)	15	142		139	192		69	88		234	97	
Number with Age Adjusted Death Rates (2014-2016)	17	166		146	224		86	97		254	116	

*Note: ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively*

[a] *Percentage changes are calculated from counties with non-suppressed death counts for both the 2011-2013 and 2014-2016 time periods*

To determine the relationship between OTP presence and rates of opioid-related deaths, a matching technique is implemented. Because we are not using experimental data in our analysis, matching controls for any selection bias or confoundedness that could skew the results (Imbens and Wooldrige, 2009). In this study, coarsened exact matching (CEM) is the primary method used to determine the causal effect of having an OTP nearby. It has been suggested that since CEM is a monotonic imbalance bounding method, it has significant advantages over other matching techniques such as propensity score matching and Mahalanobis matching (Iacus et al., 2011a). CEM's main advantage is that the balance between the treated and control groups is selected ex ante by the user, which avoids any re-estimating of the matching process in order to improve the balance in the data. The technique 'coarsens' selected variables into strata of different sizes, and only keeps observations (treated and control) with a matched counterpart in all bins. Thus, CEM is essentially a pruning technique, and is typically combined with a parametric modeling technique such as linear regression when the matching is not exact (Blackwell et al., 2012).

Determining the Impact of OTPs with CEM

The goal of the CEM methodology is to reduce the dataset to matched treated and control counties. These matched counties can then be used to estimate the association of an OTP on the county-level age-adjusted opioid death rate from 2014 to 2016; or, as an alternative metric, the percentage change between the 2011-2013 and 2014-2016 death rates. For this study, two separate treatments are considered. The first treatment is whether a county had an OTP facility in place as of 2013. As Figure 2 displays, the number of opioid deaths in the South began to increase dramatically beginning in 2013. So, we are interested in whether OTPs existing prior to the spike in opioid-related deaths have any association with future death rates[6]. As previously noted, the

[6] Ideally, we would be most interested in OTPs that came in existence after the initial spike, and measure their resulting impact. Data limitations prevent this analysis.

CEM analyses is run separately for metropolitan and non-metropolitan counties, to determine if the effect of OTPs differs between these two types of areas. The descriptive statistics for the treated and control counties for treatment 1 (OTP presence in county) are displayed in Table 2.1. 27 of the 830 non-metropolitan counties in the South (3%) are considered treated, compared with 156 of the 593 metropolitan counties (26%). Treatment 2 is the existence of an OTP in a neighboring county before 2013[7]. The purpose of including treatment 2 is to determine whether OTPs have any spillover effects on opioid death rates in surrounding areas. Rosenblum et al. (2011) found that the average travel distance of patients from their residence to an OTP was 15 miles, suggesting that patients may travel into a neighboring county in order to receive treatment. 278 non-metropolitan and 386 metropolitan counties are considered treated under this method. Descriptive statistics for the treated and control counties under treatment 2 are also listed in Table 2.1. The selected covariates that are coarsened and then used to match treated and control counties in the CEM are the county's age-adjusted opioid death rates from 2011-2013, the county's average prescription rate from 2011-2013, the log of the county's population, the percentage of the population that is white, and the poverty rate. High opioid supply in the form of excessive opioid prescriptions has been identified as a contributing factor to the U.S. opioid crisis (Maxwell, 2011; Kolodny et al., 2015;). Therefore, it is crucial to control for opioid supply via the county-level prescription rate in our analysis. Population size, percentage of the population that is white, and poverty rates have also been found to be related to the number of an area's opioid-related deaths (Paulozzi and Xi, 2008; Bohnert et al., 2011; Siegler et al., 2014; Visconti et al., 2015). When looking at the descriptive statistics in Table 2.1, the death rates between treated and control non-metropolitan counties show no statistical difference. However, treated non-

[7] A neighbor is considered to be any county that shares a border with the county of interest (queen contiguity matrix).

metropolitan counties have higher populations than control counties for both treatments 1 and 2. Treated counties also have higher prescription rates.

In CEM, it is important to note if the imbalance in covariates between the treated and control groups improves after the treated and control observations are matched and placed into strata. The L1 imbalance measure is used, with smaller values indicating less imbalance[8]. As Table 2.2 shows, the multivariate L1 imbalance measures improve after the CEM procedure for non-metropolitan counties, signaling that there is more balance in the data after matching. Appendix 2.A shows that the same result holds for metropolitan counties. The tables also indicate how many treated and control observations are included in the sample for analysis before and after the CEM. For example, the unmatched data for treatment two in the non-metropolitan sample had 278 treated and 552 control counties; this is reduced to 143 treated and 195 control after CEM (Table 2.2).

After the strata have been created, a weighted least squares regression is used to determine the treatment effects. The regression model can be specified as

$$Y_i = \alpha_i + \beta_1 T_i + \beta_2 \mathbf{X}_i + \varepsilon_i \tag{2.1}$$

where the dependent variable Y_i is either the age adjusted death rates from 2014-2016 or the percentage change between the age-adjusted 2014-2016 and 2011-2013 death rates for county i, T_i is a binary variable which takes the value of 1 if county *i* is considered treated, and $\mathbf{X}_i$ is a vector of county i's demographic variables that may influence Y_i. Following the procedure in Ford (2018), a simple specification is first carried out with T_i as the sole explanatory variable (i.e. omitting $\mathbf{X}_i$ and assuming the data has been exactly matched). A supplementary specification

[8] The L1 values are calculated by determining the difference in the empirical distributions between the treated and control groups (Iacus et al., 2011b).

Table 2.2. L1 Imbalance Measures for Non-Metropolitan Counties

	Treatment 1: OTP in County before 2013		Treatment 2: OTP in Neighboring County before 2013	
	Unmatched Data	Matched Data	Unmatched Data	Matched Data
Age Adjusted Death Rates (2011-2013)	0.25	0.00	0.21	0.03
Prescription rate	0.18	0.21	0.11	0.08
Ln(Population)	0.30	0.09	0.15	0.14
Percent white	0.10	0.13	0.08	0.05
Poverty rate	0.15	0.10	0.19	0.10
Multivariate L1	0.99	0.64	0.98	0.89
Number of Observations: Treated, Control	27, 803	10, 27	278, 552	143, 195

includes the other control variables with the argument that the CEM has not fully controlled for differences across the treated and control groups.

While CEM is a relatively new matching technique, other forms of matching have been used more extensively in the health literature. To verify the robustness of the weighted least squares models, propensity score matching (PSM) is executed. This technique first estimates the likelihood of receiving treatment (access to an OTP) via logistic regression, using the same county-level variables as in the CEM specification. The resulting probabilities are then used to match treated counties with control counterparts with similar likelihoods. Differences in county-level death rates between the matched treated and control groups then show the average treatment effect of OTP accessibility. The full sample (i.e. not reduced via CEM) is used to perform PSM for each geography (metro / non-metro), and both kernel matching and nearest neighbor matching techniques are carried out[9].

Results

Regression Results Following CEM

The weighted least squares regression results are displayed in Tables 2.3 (non-metro counties) and 2.4 (metro). There are two dependent variables of interest: (1) the age-adjusted opioid death rate from 2014-2016 and (2) the percentage change in deaths across the two periods (2011-13 to 2014-16). Note that there are typically fewer observations under this second variable, since some counties did not have death data available in both time periods. Each table contains 4 models across the 2 treatment effects. In the initial models (1) and (3), the binary treatment variable is the

---

[9] In nearest neighbor matching, treated and control observations are matched based on similarities in the covariates. A commonly used approach is to include kernel matching as a robustness check for nearest neighbor matching, because it corrects for any large differences in covariates between the treated and control units (Whitacre et al., 2014). Kernel matching determines the distance between one treatment observation and many control observations, and gives the closer units a higher weight in the matching procedure.

Table 2.3. Regression Results for Non-Metropolitan Counties following CEM

	Age Adjusted Deaths (2014-2016)		Percentage Change in Deaths	
	(1)	(2)	(3)	(4)
Treatment 1: OTP in County before 2013	5.65	10.87**	20.28	14.28
Age Adjusted Death Rates (2011-2013)		0.42		-1.34
Prescription rate		0.17		-0.41
Ln(Population)		6.01		44.15
Percent white		0.42		2.01
Poverty rate		1.90**		9.62**
Constant	17.84***	-150.99*	21.46	-716.28*
Number of Observations	18	18	18	18
R^2	0.03	0.87	0.04	0.61
	(5)	(6)	(7)	(8)
Treatment 2: OTP in Neighboring County before 2013	0.24	1.60	8.62	7.42
Age Adjusted Death Rates (2011-2013)		0.75		-0.95
Prescription rate		-0.12*		-0.91*
Ln(Population)		-7.42		-10.52
Percent white		-0.10		-0.28
Poverty rate		0.10		2.62
Constant	16.52***	98.46	25.53**	245.93
Number of Observations	65	39	39	29
R^2	0.00	0.43	0.01	0.23

*Note: ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively*

Table 2.4. Regression Results for Metropolitan Counties following CEM

	Age Adjusted Deaths (2014-2016)		Percentage Change in Deaths	
	(1)	(2)	(3)	(4)
Treatment 1: OTP in County before 2013	0.30	0.64	7.60	4.08
Age Adjusted Death Rates (2011-2013)		1.15***		-5.39
Prescription rate		0.05		0.47
Ln(Population)		-0.31		0.49
Percent white		-0.01		0.67
Poverty rate		-0.20		-0.30
Constant	11.08***	4.65	54.66***	4.87
Number of Observations	62	60	60	60
R^2	0.00	0.67	0.00	0.08
	(5)	(6)	(7)	(8)
Treatment 2: OTP in Neighboring County before 2013	0.19	0.18	19.58	23.30
Age Adjusted Death Rates (2011-2013)		1.09		-7.42*
Prescription rate		0.06*		0.70
Ln(Population)		0.60		21.12
Percent white		-0.01		0.92
Poverty rate		-0.20		-3.20
Constant	13.15***	-5.56	61.11***	-223.68
Number of Observations	68	57	57	57
R^2	0.00	0.46	0.02	0.18

*Note: *** represents statistical significance at the 1%*

only explanatory variable, along with a constant term. In Table 2.3, none of the coefficients for the treatment variable are statistically significant in the simple regression models, showing that a county's opioid related death rates are not associated with having an OTP within their borders or in a neighboring county. This result does not hold in model (2) when the specification is expanded to include the county-level variables that were matched on during CEM. In model (2), the coefficient on treatment 1 is positive, and statistically significant. Thus, the presence of an in-county OTP as of 2013 is associated with higher opioid-related deaths in 2014 through 2016. This result is similar to those for previous studies in metropolitan areas, which found that increased access to substance use treatment is related to undesirable outcomes for patients with substance use disorders (Stahler et al., 2007; Kao et al., 2014).

Robustness Check with Propensity Score Matching

Appendix 2.B contains the results of the first-stage logistic regression for the PSM technique, where population and the prescription rate prove to be an important predictor of OTP availability. Tables 2.5 and 2.6 display the PSM results, which generally confirm the findings of the CEM-based regressions. The differences between treated and control counties are mostly never statistically significant, regardless of metro / non-metro location or matching technique used. Two cases which do indicate a statistically significant association between OTP presence and the opioid death rate are seen in Table 2.5. For treatment 2, a positive difference is seen between treated and control counties. This finding implies that non-metropolitan counties with a neighboring OTP as of 2013 are associated with increased incidences of future opioid-related mortality. In aggregate, none of the modeling techniques implemented found that treatments 1 and 2 have a statistically significant negative association with the rate of, or change in, opioid-related deaths in Southern counties.

Discussion

Table 2.5. Matching Estimator Results for Non-Metropolitan Counties

	Nearest Neighbor					Kernel				
	Treated	Control	Difference	T-stat		Treated	Control	Difference	T-stat	
Treatment 1: OTP in County before 2013										
Age Adjusted Death Rate (2014-2016)	21.66	17.59	4.07	0.79		21.66	19.28	2.39	0.53	
Percent Change in Deaths	20.35	15.49	4.86	0.30		20.35	17.61	2.75	0.21	
Number of Observations	15	112				15	112			
Treatment 2: OTP in Neighboring County before 2013										
Age Adjusted Death Rate (2014-2016)	23.20	16.76	6.44	2.22	**	21.02	18.39	2.62	1.09	
Percent Change in Deaths	22.17	7.27	14.90	1.54		23.83	6.24	17.59	1.77	*
Number of Observations	60	67				55	67			

*Note: ** and * represents statistical significance at the 5% and 10% level, respectively*

Table 2.6. Matching Estimator Results for Metropolitan Counties

	Nearest Neighbor				Kernel			
	Treated	Control	Difference	T-stat	Treated	Control	Difference	T-stat
Treatment 1: OTP in County before 2013								
Age Adjusted Death Rate (2014-2016)	13.88	11.70	2.18	0.72	13.88	12.12	1.76	0.72
Percent Change in Deaths	62.76	64.51	-1.75	-0.08	62.76	58.57	4.19	0.26
Number of Observations	138	177			138	177		
Treatment 2: OTP in Neighboring County before 2013								
Age Adjusted Death Rate (2014-2016)	14.27	15.87	-1.60	-0.81	14.34	16.76	-2.42	-1.35
Percent Change in Deaths	52.83	57.38	-4.55	-0.41	53.63	52.24	1.39	0.14
Number of Observations	222	93			220	93		

This study provides a first look at OTP effectiveness in the South census region, specifically asking whether increased access to treatment is associated with opioid-related death rates for both metropolitan and non-metropolitan counties. To simulate an experiment for analysis, two distinct treatments are considered: (1) an in-county OTP in 2013, and (2) a neighboring county OTP in 2013. The results from a variety of matching and regression techniques suggest that there are no robust, measurable association between OTPs and lower opioid-related deaths for any of the treatments or locations considered.

These results are likely to be viewed as a disappointment to proponents of medication-assisted treatment, particularly to those advocating for more OTP facilities in rural locations. However, a thorough empirical assessment of varied opioid treatment options – and comparison of outcomes across options – is crucial to developing an appropriate framework of policies. Additionally, as states and regions continue to respond to the opioid crisis, it is important to have baseline data for comparison purposes. For example, the analysis here was limited by having only 27 non-metro counties in the South with OTP sites as of 2013, which led to a small number of observations in our regression models. The most current (2018) National Directory of Drug and Alcohol Treatment Facilities now shows that 50 non-metro counties in this region have OTPs, and it may be possible that newly added programs will have a measureable effect on opioid deaths. If so, understanding what changed would be an important policy consideration.

We note that our results do not necessarily imply that rural areas with a lack of existing treatment options should avoid OTPs, or that OTPs should not be targeted for these locations. Unlike the findings of Martinson (1974), which were generalized to state that treatment is not effective in prison recidivism, the conclusions from this study should not be used to say that OTPs are not worthwhile investments. First, our research focuses only on opioid-related deaths. There are other meaningful opioid-related outcomes without easily accessed data at the county level, such as addiction, relapses, or overdoses (but not deaths). Several studies have demonstrated that MAT can curb opioid misuse – which is another important component of the crisis (Schwartz et al., 2013; Volkow et al., 2014). Second, there are several possible outside factors for why OTPs are not shown to have an effect on opioid deaths in this study, which should be researched further. As previous studies have mentioned, deterrents to attending treatment in rural locations can be the high cost of treatment, transportation barriers, and the limited number of services available (Jackson and Shannon, 2012; Browne et al., 2016; Moody et al., 2017). Future work should explore the degree to which these obstacles impact the number of patients able to receive treatment at an OTP.

Another hindrance to OTPs' effectiveness could be societal factors that either prevent a patient from going to treatment, or encourage them to relapse once their treatment is completed. Opioid-dependent rural patients have expressed that there is stigma surrounding attending treatment which is heightened in close-knit communities (Jackson and Shannon, 2012; Browne et al., 2016; Rigg et al., 2018). This stigma can deter those who are opioid-dependent from seeking the necessary assistance, or continuing treatment once it has begun. Studies in urban cities have shown that substance use treatment centers tend to locate in places with high levels of criminal activity, which can lead to continued drug misuse after treatment completion (Jacobson, 2006; Kao et al., 2014). Previous work has identified how the culture of rural regions can promote opioid misuse (Keyes et al., 2014; Monnat and Rigg, 2016), but no work to date has specifically examined the cultural environment of the rural cities with treatment centers. This is an additional area for future research.

Limitations for the analyses in this study should also be considered. Our work is limited by the CDC suppression of county-level death counts which are less than ten. As previously stated, a majority of the counties in the South had suppressed death counts for the aggregated years 2011-2013 (66%) and 2014-2016 (61%). Appendix C shows a comparison of demographic differences between counties with suppressed and non-suppressed data shows that some differences do exist, although they are typically small in magnitude. This suggests that the findings here may not be applicable to all counties in the Southern region. This limitation should ease as more data is collected and aggregation across even more years becomes possible; alternatively, the CDC offers restricted-access to the data which requires project approval and a confidentiality agreement. An additional data-related limitation concerns the information provided in the National Directory of Drug and Alcohol Abuse Treatment Facilities. The directory does not provide information about an individual facility's number of treated patients per year, or number of medical professionals on staff – which could have an impact on an OTP's effectiveness in reducing opioid misuse. A final limitation for this study is its inclusion of only one census region. Our results only hold for the South census region counties with available opioid-related death rate data, and future work should consider other regions to determine if OTP impacts vary geographically. Addressing the growing opioid crisis requires examining the outcomes associated with treatment options for misusers, and this analysis should be considered a first step in empirically assessing one major method currently in use. Similar analysis should follow for other treatment options.

CHAPTER III

DO PRESCRIPTION DRUG MONITORING PROGRAMS ENCOURAGE ILLICIT OPIOID ABUSE?

As the opioid epidemic has expanded across the U.S., states have intervened by enacting legislation and establishing programs aimed at curtailing the crisis. Currently, forty nine U.S. states and D.C.[10] have operational statewide prescription drug monitoring programs (PDMPs) in an effort to thwart prescription opioid abuse. PDMPs are statewide electronic databases that store information on prescriptions for controlled substances, with data coming from the dispensing pharmacies. PDMPs are useful in identifying patients who are misusing prescription opioids or "doctor shopping", and in recognizing doctors who are overprescribing opioid medications. Doctor shopping and overprescribing have both been linked to increased incidences of patient misuse and overdose (Edlund et al., 2007; Dunn et al., 2010; Peirce et al., 2012; Miller et al., 2015). Other uses for PDMPs are to reduce drug diversion, detect patients who require prescription opioids for legitimate medical reasons, and to inform public health policies by

---

[10] Missouri is the only state without a statewide PDMP program. St. Louis County operates a PDMP which includes 72 jurisdictions within the state as of February, 2019. (St. Louis County Prescription Drug Monitoring Program, 2019).

identifying trends in drug use and misuse (Finklea, 2014).

The main objective of this study is to assess the relationship between the strength of a state PDMP program (measured by the number and robustness of PDMP regulations) and two types of opioid overdose deaths from 1999 to 2016: prescription vs. heroin. In recent years, researchers have observed a shift away from deaths caused by prescription opioids to deaths caused by illicit opioids, like heroin (Dasgupta et al., 2014; Maxwell, 2015). Figure 3.1 displays trends in the prescription- and heroin- related age adjusted death rate in the U.S. during our study period, using data from the Centers for Disease Control and Prevention's (CDC's) multiple cause-of-death mortality files. From 2010 to 2016, the heroin death rate has seen a five-fold increase, while the prescription opioid death rate has less than doubled. Thus, beginning in 2010, heroin deaths have risen at a quicker rate than prescription opioid deaths. However, the heroin-related death rate is still below the prescription-related death rate.

Past studies have found a positive link between the implementation of PDMPs and these increased rates of heroin misuse (Ali et al., 2017; Faryar et al., 2017; Victor et al., 2017; Branham, 2018). That is, states that have enacted PDMPs have seen their heroin-related deaths increase. An explanation behind this relationship between PDMPs and heroin use are that PDMPs make accessing prescription drugs more difficult, so those who misuse these medications switch to using heroin. Many heroin users began through misusing prescription opioids (Pollini et al., 2011; Lankenau et al., 2012; Jones, 2013; Muhuri et al., 2013;), so this reasoning is certainly plausible. As opposed to these previous works, our analysis looks at the impact of a combination of many different PDMP regulations instead of the effect of general PDMP enactment.

This paper expands upon a previous study (Pardo, 2017) which used a series of fixed effects models to examine how PDMP robustness affected the prescription opioid overdose death rate at the state level. We expand upon the Pardo paper in three ways: 1) additional outcome variables,

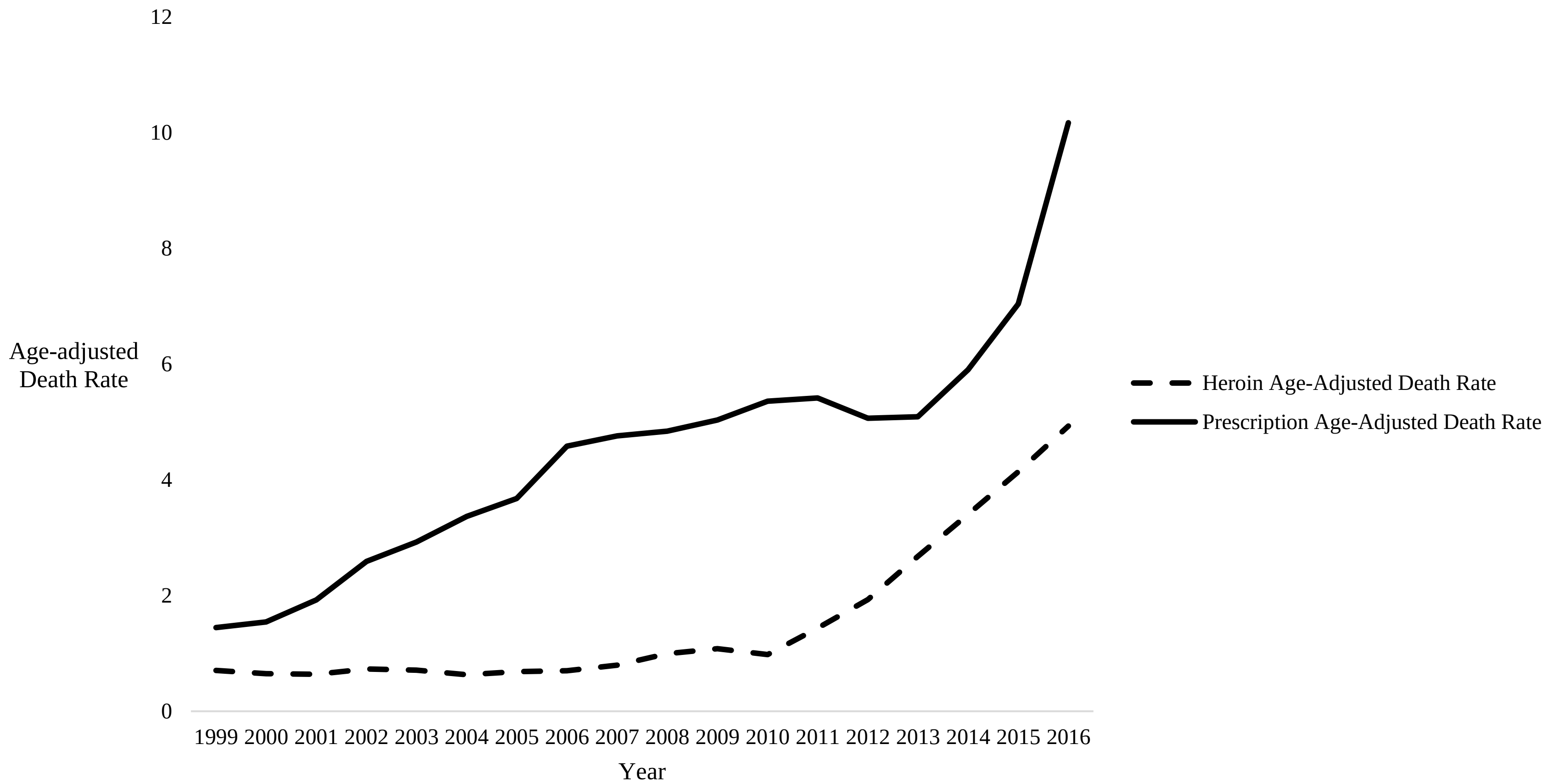


Figure 3.1. Prescription Opioid- and Heroin-Related Age-adjusted Death Rates, 1999-2016

2) a more analytical approach to generating the PDMP robustness score, and 3) additional years of data. In our fixed effects models, we use the heroin death rate (along with the prescription opioid death rate) as the outcome variable to determine if PDMP strength is associated with higher (or lower) mortality incidences. To create the measure of PDMP strength, Pardo aggregated the number of state PDMP regulations, with ad hoc weights assigned to different legislative components. As an alternative to that approach, this study uses multiple correspondence analysis (MCA) to generate the score of PDMP robustness. MCA is an extension of principal component analysis (PCA), and is used to identify latent variables of state PDMP strength by analyzing the same set of PDMP regulations assessed by Pardo. Incorporating MCA maximizes the correlations between the variables that went into the formation of Pardo's score, and will provide an alternative (and likely more robust) measure of the intensity of a state's PDMP throughout the years.

Another extension of Pardo's work is the use of a larger and more current sample of data. In his work, Pardo used a panel dataset that covered PDMP legislation, prescription overdose death rates, and state demographic variables from 1999 to 2014. Our panel dataset covers the years 1999 to 2016, which notably includes two additional years of data as the opioid crisis continued to grow. For our analysis, two series of fixed effects models are conducted: one using our MCA-generated score as the measure of PDMP strength, and the other using Pardo's score for comparative purposes. Maps are also created to determine if any spatial correlations exist between the MCA-generated scores and opioid-related deaths.

Evaluating the Mixed Evidence: The Impact of State PDMPs

Previous research has come to conflicting conclusions when examining opioid-related outcomes in states with operational PDMPs versus those without PDMPs in place. Reisman et al. (2009) found that states with PDMPs had lower rates of admissions to substance abuse treatment programs for prescription drug abuse when compared to states with no operational PDMP programs during the period 1997 to 2003. Yet, when looking at the U.S. Drug Enforcement Agency (DEA) Automation of Reports and Consolidated Orders System (ARCOS) data, their analysis indicated that states with PDMPs had an overall increase in opioid shipments[11]. Thus, their findings imply that physicians were not deterred from prescribing opioid medications due to PDMPs. This early finding regarding how PDMP programs influence the amount of prescriptions for opioid medications has been supported and contradicted in the later PDMP literature. Brady et al. (2014) showed that the enactment of a state wide PDMP from 1999 to 2008 had no significant effect on the amount of opioids dispensed per capita. Similar to Reisman et al. (2009), Brady et al. (2014) also used DEA ARCOS data in their studies, however, the researchers differed in the specific opioid medications they tracked in their analysis. Conversely, several studies demonstrate that there is a significant reduction in the number of prescriptions for Schedule II opioids following the implementation of a PDMP program (Bao et al., 2016; Wen et al., 2017). Bao et al. (2016) looked at the effect of PMDP implementation on opioid prescribing in ambulatory medical centers, whereas Wen et al. (2017) examined the issue in the context of how implementation impacts such prescriptions for Medicaid patients.

Other researchers have focused on how the existence of a state PDMP influences opioid misuse and mortality. Similar to the findings on a PDMP's effect on opioid prescriptions, the relationship between having an operational PDMP and nonmedical and illicit opioid use is unclear. It has been suggested that PDMPs are not associated with fewer prescription opioid-related deaths (Paulozzi et al., 2011; Brown et al., 2017). However, Patrick et al. (2016) did find that PDMP implementation led to a decrease in prescription opioid overdose deaths in the year after the PDMP became operational. Paulozzi et al. (2011) and Patrick (2016) both conducted their analysis using multiple states, however, Patrick (2016) only looked at thirty-four states that

[11] Opioid shipments (in grams) are tracked from their manufacturer to point of sale location.

implemented PDMPs between 1999 and 2013, whereas Paulozzi et al. (2011) used all fifty states (plus D.C.) in their analysis. Delcher et al. (2015) concentrated specifically on overdose deaths due to oxycodone, and looked at how they were affected after Florida began their PDMP program in 2011. They found that the PDMP in Florida was successful in reducing oxycodone-related mortality. When measuring how PDMPs impact treatment admissions for opioid-use disorders, two studies came to conflicting conclusions. Reifler et al. (2012) found that PDMPs are effective in reducing admissions to opioid treatment programs, whereas Branham (2018) observed that PDMP implementation was associated with more patients going to treatment centers due to prescription opioids or heroin. Reifler et al. (2012) used data from the Researcher, Abuse, Diversion, and Addiction-Related Surveillance (RADARS) System that looked at treatment admissions from 2005 to 2009, while Branham (2018) used the Treatment Episodes Data Set which covered years 1992 to 2012. Concerning the frequency of opioid misuse, Ali et al. (2017) found that PDMPs were associated were fewer days of prescription opioid misuse in the past year, but more days of heroin use, using survey data from the National Survey of Drug Use and Health. It is also important to consider the findings from Pardo (2017). The fixed effects models in their study show that continuous measures of PDMP score are negatively associated with prescription-opioid related deaths. When PDMP scores are broken into quartiles, only the third quartile of scores is statistically negatively related to the death rate. After looking at previous studies, it is apparent that the literature is conflicted about whether PDMPs are useful in reducing opioid misuse. This study contributes to this body of work through using a nationwide sample of states, and evaluating how a range of PDMP regulations is associated with opioid-related mortality. This should provide insight on the effectiveness of overall PDMP strength, as opposed to a simple binary measure of PDMP presence.

Data

Panel data for this study regarding the features of state PDMP regulations, prescription opioid and heroin age adjusted death rates per 100,000 residents, and demographics are gathered for years 1999 through 2016. All data is aggregated at the state level for analysis. With 51 states (D.C. is included in our analysis) and 18 years of data, 918 observations are included in our sample. The Prescription Drug Abuse Policy System (PDAPS) and Brandeis University PDMP Training and Technical Assistance Center webpages are used to determine which year the state PDMP became operational[12], and the regulations that apply to each state's PDMP. Eleven different state PDMP regulations are examined. Following Pardo, each of the eleven regulations is weighted based on existing evidence or beliefs that they are effective in reducing opioid overdose deaths or changing how opioid medications are prescribed by physicians. Examples of such regulations are if the PDMP monitors more than Schedule III drugs, how often data has to be reported from dispensing pharmacists to the PDMP, and if the PDMP has an oversight board.

PDAPS is also used to create additional explanatory variables in our fixed effect models, such as the agency in charge of running the state PDMP. Other explanatory variables that come from PDAPS are indicators that show if a state has laws that allow access to naloxone, Good Samaritan laws related to opioid overdoses, pain clinic management laws, and medical marijuana dispensary laws. Studies have identified these categories of legislation as having the potential to reduce the number of opioid related overdoses and deaths (Okie, 2010; Hewlett et al., 2013; Compton et al., 2015; Powell et al., 2018).

To determine each state's age adjusted prescription and heroin opioid death rate for 1999 through 2016, the National Vital Statistics System (NVSS) multiple cause-of-death mortality files are accessed through the CDC Wide-ranging Online Data for Epidemiologic Research (WONDER) database. Each death certificate is classified on the WONDER database with the person's cause

---

[12] If a regulation began after July 31st, then it was not considered to be in effect for that year. This coding ensures that the regulations were in place for more than five months out of the year.

of death, using the coding scheme found in the International Classification of Diseases, tenth revision (ICD-10). Deaths found with an underlying cause of death related to drugs or alcohol are first selected[13], and are then narrowed down to just deaths related to prescription opioids or heroin[14]. A limitation when working with the CDC WONDER database is that data suppression occurs when a death count for an area is less than ten. In our sample, about 4% and 37% of the 918 observations have death counts less than ten for prescription opioid and heroin deaths, respectively. Following Pardo (2017), we apply a death count of five for these observations. Data suppression is also an issue in terms of the calculation of age adjusted death rates. The WONDER database does not make available age adjusted death rates when death counts are less than twenty, which accounts for about 8% of our prescription opioid deaths and 44% of our heroin deaths. Because crude death rates are oftentimes relatively similar to the age adjusted death rates[15], if an observation has a death count of less than twenty, the crude death rate per 100,000 residents is used in its place.

Three state demographic variables are also collected: the percentage of the population who is white, median household income, and percentage of the population who has at least a high school education. An area's percentage of white residents and its educational attainment levels have been found to be determinants of prescription opioid related deaths in previous studies (Bohnert et al., 2011; Lanier et al., 2012). With respect to median household income, higher socioeconomic status has been linked to the probability of receiving an opioid prescription during an emergency

[13] The ICD-10 codes for drug and alcohol induced deaths that are gathered for this study are: X40-X44 (Unintentional), X60-X64 (Suicide), X85 (Homicide), and Y10-Y14 (Undetermined).
[14] The ICD-10 codes for prescription opioid deaths that are gathered for this study are: T40.2 (Other opioids), T40.3 (Methadone), and T40.4 (Other synthetic narcotics). The ICD-10 code for heroin deaths is T40.1 (Heroin).
[15] Age-adjusted and crude death rates differ due to age-adjusted death rates adjusting for the state's differences in age distributions (Anderson and Rosenberg, 1988). Crude death rates are simply calculated by taking the number of deaths in a state in a given year and dividing it by the state's population during that time period, then multiplying the resulting value by 100,000.

department visit for pain management (Joynt et al., 2013). Annual data for these three variables comes from U.S. Census intercensal estimates.

Methodology

Using MCA to Create a Score of PDMP Robustness

To provide another score of PDMP fitness, we use MCA to create a score for each state in a given year. MCA has been used to create indices to measure a person's health (Kohn, 2012), and a household's socioeconomic status (Cortinovis et al., 1993; Ezzari and Verme, 2012) but has never been used previously, to our knowledge, to examine a state-wide program. The general rationale behind using MCA is to identify a latent variable by combining a series of variables together that relate to the underlying measure they are trying to quantify. For example, Kohn (2012) aggregated variables such as a person's self-reported health, number of accidents they were in during the past year, disability status, and if they were a smoker or not to derive his health index. So, for the purposes of this research, we are identifying a latent variable of state PDMP strength by examining a variety of PDMP regulations.

These scores generated through MCA are compared to the scores generated using Pardo's methodology to determine if model estimates and fit change with this alternative measure of PDMP robustness. The basis behind using MCA in this study is to combine the eleven categorical variables that went into Pardo's score, but in a way that maximizes the correlations between them. Thus, we are able to use the relationships between the variables and the dimensions they are in as weights when creating our PDMP score, which is an improvement over Pardo's method of assigning his variable weights, based on perceived importance.

The procedure behind implementing MCA is similar to that of PCA, which is a widely used technique to combine multiple variables to derive a latent variable of interest, while still retaining the most information from your data. PCA is not incorporated into this study, however, because it

Table 3.1. PDMP Regulations, Weights, and MCA Coordinate Values

Regulation Categories	Weight	Standard Coordinate from MCA
Schedule3: Monitors more than Schedule III drugs		
No	0	0.23
Yes	3	1.61
Disclosure: Required to identify suspicious PDMP behavior		
No	0	0.73
Yes	1	1.35
Accessbypolice: Law enforcement and prosecutors can access PDMP		
No	0	1.11
Yes	1	1.15
Accessbyprescribers: Physicians can access PDMP		
No	0	1.21
Yes	1	1.26
Frequency: How often data has to be reported to the PDMP		
Not required	0	1.18
Monthly	1	0.23
Less than a month, greater than a week	2	0.81
Weekly	3	1.63
Daily	4	1.89
Live system	5	0.78
Prescribe: Prescribers have to check PDMP before writing prescriptions		
No	0	0.11
Yes	4	2.33
Share: Allowed to share data with other state PDMPs		
No	0	0.48
Yes	1	1.80
Evaluation: Prone to program evaluations		
No	0	0.33
Yes	1	1.85
Oversight: Has an oversight board		
No	0	0.48
Yes	1	1.66
Retention: Length of data retention in PDMP		
No operational PDMP	0	1.47
No timeframe specified but PDMP is operational	1	0.91
1 year or less	2	1.89
Between 1 to 2 years	3	0.55
Between 2 to 5 years	4	1.62
5 years or more	5	1.27
Funding: Source of PDMP funding		
No funding is given	0	0.87
Grants or gifts	1	1.38
Charging fees	2	1.32
Appropriated funds	3	1.30

works best for normally distributed, continuous variables whereas MCA is suited for categorical variables (Hill and Smith, 1976; Kolenikov and Angeles, 2004; Abdi and Valentin, 2007; Sourial et al., 2010). The first step in MCA is to determine the dimensions (linear combinations) of your variables, which signals how much principal inertia (or variance) is captured within them. We only use coordinate scores from the first dimension, since it captures over 85% of the principal inertia in our variables. Next, the MCA coordinates are extracted and become weights for the categorical variables. Coordinates are similar to factor loadings in PCA, and are correlation coefficients between the categorical variables' responses and the dimension you are examining. Following Seplaki et al. (2013), coordinates are standardized and multiplied by negative 1. Therefore, higher coordinates indicate a stronger PDMP. Table 3.1 displays the eleven regulations included in our analysis, along with their categories. The weights and standardized MCA coordinates are also included. It is important to note that the weights shown in Table 3.1 are the similar to the weights Pardo (2017) used to create their study's score of PDMP robustness[16].

To determine the score for each regulation, the coordinate values are multiplied by Pardo's weights for the responses, which indicate whether they have the statute for their PDMP or what category of regulation they have. For example, if a state's PDMP monitored more than Schedule III drugs in a given year, then their score for that regulation would be 4.83 (the weight of 3 multiplied by the standard coordinate of 1.61). Each observation in the panel dataset therefore has their own MCA-generated score. Because we are working with panel data in our analysis, there is a question about whether to run MCA for the entire sample, or to split the data into cross sections by year and then perform the MCA. As noted in Kohn (2012), it is appropriate to keep the pooled

[16] During the data exploration process, discrepancies were discovered between the weights that Pardo assigned to the regulations and the corresponding descriptive statistics. In order to reproduce Pardo's descriptive statistics, the weights were modified to fit their findings. The weights for the regulations *Disclosure*, *Frequency*, and *Retention time* were adjusted, and are different than the weights Pardo used in their analysis.

sample for MCA when your variables are linked between years. Since the PDMP regulations used in this study typically did not change for a state once it was implemented[17], we use the full sample of observations for our MCA. Once the products of MCA coordinates and response weights are calculated for the eleven regulations, they are summed together for a final score of PDMP intensity. This technique is similar to how Kohn (2012) created their health index.

Fixed Effects Models with PDMP Scores

For analyzing the effect of our PDMP score on state age adjusted prescription opioid and heroin death rates, we follow Pardo (2017) in estimating two-way fixed effects models. One fixed effect is at the state level, and the second is a time fixed effect. The time fixed effects ease concerns for reverse causality in the models, due to controlling for any unobserved heterogeneity between the sample years. Explanatory variables include our generated PDMP score from the MCA and binary indicators for the agency that operates the state PDMP. The categories of different agencies include law enforcement agencies, the Department of Health, Consumer Protection offices, and professional and licensing boards. An 'Other' category is also included if the agency in charge of the PDMP falls outside of the aforementioned categories. Other explanatory variables are the demographic variables from the U.S. Census (percentage of population who are white, median household income, and percentage of population with a high school degree) and indicators for if a state has naloxone access, Good Samaritan, pain clinic management, or medical marijuana laws. Table 3.2 displays the descriptive statistics for the variables included in the fixed effects models. Means and standard deviations are calculated for all of the observations in the sample, and also broken into observations with and without operational PDMPs for comparative purposes.

[17] One regulation that did change throughout the years was Frequency, which denotes how often dispensers have to report data to the PDMP.

Table 3.2. Descriptive Statistics for Variables in Fixed Effects Models

	All observations n = 918		No Operational PDMP n = 379		Operational PDMP n = 539	
Variable	Mean	SD	Mean	SD	Mean	SD
MCA Score	8.18	9.23	-	-	13.93	8.05
Pardo Score	5.93	6.05	-	-	10.10	4.48
Schedule 3	0.38	0.99	-	-	0.64	1.23
Disclosure	0.35	0.48	-	-	0.60	0.49
Access by police	0.49	0.50	-	-	0.83	0.37
Access by prescribers	0.49	0.50	-	-	0.84	0.37
Frequency	1.24	1.43	-	-	2.12	1.27
Prescribe	0.18	0.84	-	-	0.31	1.07
Share	0.21	0.41	-	-	0.36	0.48
Evaluation	0.15	0.36	-	-	0.26	0.44
Oversight	0.22	0.42	-	-	0.38	0.49
Retention time	1.36	1.70	-	-	2.31	1.66
Funding	0.85	1.15	-	-	1.45	1.18
Naloxone	0.18	0.38	0.04	0.19	0.28	0.45
Samaritan	0.14	0.34	0.03	0.18	0.21	0.41
Pain clinic laws	0.07	0.25	0.01	0.11	0.10	0.31
MMJ dispensary	0.25	0.43	0.18	0.38	0.30	0.46
White	79.59	13.77	80.23	13.73	79.14	13.79
Income	56,624.31	8,719.96	57,678.02	9,206.33	55,883.39	8,289.82
Education	86.86	3.71	86.98	3.66	86.78	3.75
ln(Prescription Death Rate)	1.35	0.82	1.02	0.80	1.57	0.76
ln(Heroin Death Rate)	-0.22	1.18	-0.59	1.10	0.04	1.17

The general specification for the fixed effects models can be written as

$$(3.1) \quad \ln(death\ rate_{it}) = \beta_0 + \beta_1 Score_{it} + \sum_{k=1}^{4} \beta_{2_k} Agency_{\mathrm{itk}} + \delta \mathbf{Laws_{it}} + \gamma \mathbf{Demographics_{it}} + \tau_t + u_i + \varepsilon_{it}$$

with the dependent variable, the log transformation of the prescription opioid or heroin age adjusted death rate for state *i* and year *t*, being a function of the PDMP score (either from MCA or via Pardo's methods), a dummy variable for which state agency is in charge of operating the PDMP, a vector of the indicator variables for the laws that could potentially impact the opioid death rate, a vector of state demographic variables, a vector of year effects (τ_t), a vector of state effects (u_i), and an error term.

Following the model specifications in Pardo (2017), the first two models leave the MCA or Pardo score ($Score_{it}$) as a continuous variable, with model one omitting the binary indicators for which state agency operates the PDMP and model two including those indicators. Models three and four switch from using a continuous score measure to assessing it via quartiles, with model three not including the binary indicators for state agency, and model four including all of the explanatory variables.

Fixed Effects Models with Mandatory Prescriber Use Variable

Looking at Table 3.1, the largest standard coordinate from the MCA is 2.33, which is for the variable Prescribe. This variable signals if state PDMPs require that prescribers check the PDMP before writing prescriptions for controlled substances to patients. Previous studies have found an association between the mandatory review of state PDMPs and reductions in prescription opioid misuse (Ali et al., 2017; Dowell et al., 2016; Grecu et al., 2019). A decrease in the amount of prescribed and dispensed opioids has also been observed as a result of compulsory physician use of PDMPs (Rasubala et al., 2015; Winstanely et al., 2018). Faryer et al. (2017) and Victor et al.

(2017) specifically examined how Kentucky's mandated physician use of their PDMP prior to prescribing opioids impacted opioid misuse. Both studies found similar results - that nonmedical prescription opioid use decreased; however, heroin use increased after the regulation went into effect.

Because of the observed importance of the mandatory querying of PDMPs before writing prescriptions both in the literature and in our MCA, an argument can be made that separate fixed effects models should be executed using the Prescribe variable as the sole measure of PDMP strength. A binary indicator variable is created, and included alongside the other explanatory variables in the fixed effects models ran with the Pardo and MCA measures of PDMP robustness. The specification for this model can therefore be specified as

$$(3.2) \qquad \ln(death\ rate_{it}) = \beta_0 + \beta_1 Prescribe_{it} + \sum_{k=1}^{4} \beta_{2_k} Agency_{\mathrm{itk}} + \delta \mathbf{Laws_{it}} + \gamma \mathbf{Demographics_{it}} + \tau_t + u_i + \varepsilon_{it}$$

where the outcome and explanatory variables are the same as Model (3.1), with the exception of the binary $Prescribe_{it}$ variable in place of the Pardo and MCA generated PDMP scores. Therefore, with Model (3.2), we are able to determine if requiring physicians to access the PDMP has any significant effect on both prescription opioid and heroin deaths. This is different from the interpretation of β_1 in Model (3.1), which is a broader measure of how a PDMP's overall strength is associated with opioid-related deaths.

Results

Prescription Opioid and Heroin Death Rate and PDMP MCA Score Maps

Six maps are displayed in Figure 3.2 that show the prescription opioid and heroin age adjusted death rates, and MCA-generated PDMP scores at the beginning and end of our sample period. The left-hand side of Figure 3.2 shows the maps for 1999, whereas the right-hand is for 2016.

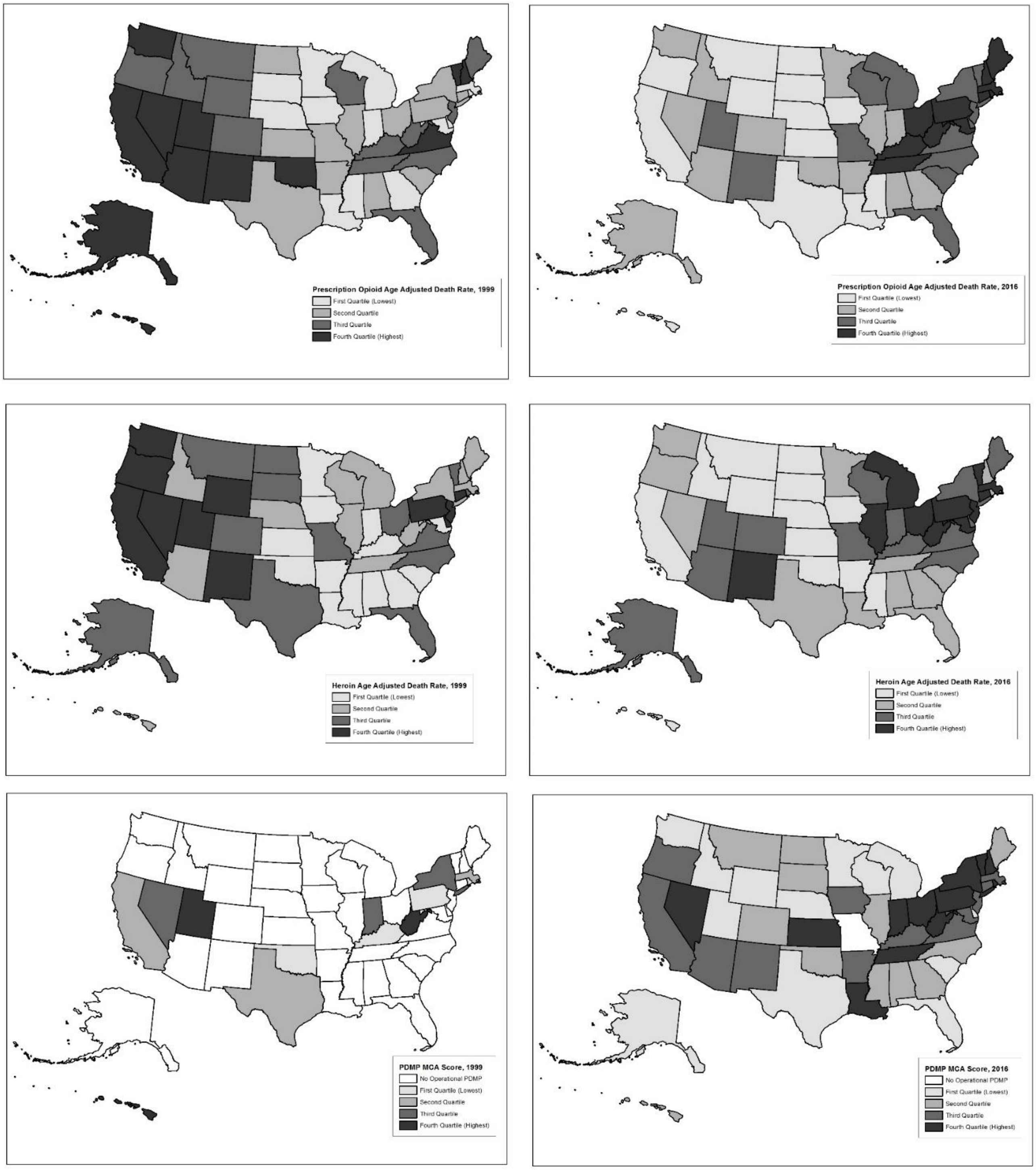


Figure 4.2. Prescription Opioid and Heroin Age-adjusted Death Rates, and PDMP MCA Scores, 1999 and 2016

Looking at the maps for 1999, states with higher quartiles of PDMP scores are seen across the U.S., with Hawaii, Utah, and West Virginia standing out as having the largest scores. Alternatively, states with high incidences of prescription opioid- and heroin-related deaths are primarily located in the West. It should be noted that 7 and 8 of the states in the fourth quartile of prescription opioid and heroin death rates in 1999, respectively, did not have operational PDMPs during that time.

Bivariate Moran's I measures are calculated to verify if any spatial correlations exist between the MCA-created PDMP scores and prescription opioid- and heroin-related deaths. The bivariate Moran's I measure is an estimate that goes from -1 to 1 and measures the spatial relationship between two variables. An estimate of -1 represents negative spatial autocorrelation where high values of one variable are surrounded by low values of the other, a value of 0 indicates no spatial autocorrelation, and an estimate of 1 signals positive spatial autocorrelation amongst the two variables. Following the common approach to determine the statistical significance of the bivariate Moran's I estimates (Anselin, 1995; Sridharan et al., 2007; Loughnan et al., 2008), 999 permutations are generated using Monte Carlo randomization to create a reference distribution. For 1999, the bivariate Moran's I between PDMP scores and the heroin-related death is 0.18, and statistically significant at the 1% level. The bivariate Moran's I between PDMP scores and prescription opioid-related deaths is 0.14 and statistically significant at the 5% level. The measures indicate that there exists a slight positive spatial autocorrelation between PDMP scores and opioid-related deaths in 1999.

Moving to the maps for 2016, a clear pattern of high rates of prescription and heroin deaths is seen in the Appalachian and Northeast regions of the country. Similarly, states in the fourth quartile of PDMP scores are clustered in those regions and the surrounding areas. However, Louisiana, Kansas, and Nevada are also in that fourth quartile of highest PDMP scores – even though their prescription opioid and heroin death rates fell in the first or second quartiles. States in the third quartile of PDMP scores are dispersed throughout the country. Therefore, in 2016, states with higher PDMP scores oftentimes experiences higher incidences of prescription opioid- and heroin-related deaths, however, this relationship is not absolute. Bivariate Moran's I values for 2016 are 0.35 and 0.31 between PDMP scores and prescription opioid- and heroin-related deaths, respectively. Both measures are statistically significant at the 1% level. These measures also indicate a small positive spatial autocorrelation between PDMP scores and opioid-related deaths. The bivariate Moran's I values in 2016 are also larger than the ones in 1999, indicating an increased incidence of states with higher PDMP score being surrounded by states with high opioid-related deaths as time progressed.

Fixed Effects Models with PDMP Scores Model Estimates

Table 3.3 displays the model estimates when the created MCA score is used as the measure of PDMP robustness, and Table 3.4 displays the estimates when the replicated Pardo score is used. As seen in Table 3.3, the continuous measure of PDMP vigor generated through MCA indicate that more state regulations are significantly associated with higher levels of heroin-related deaths in Model II. This finding lends some support to the hypothesis that as PDMPs become more stringent, heroin deaths rise as a result of prescription opioids being more difficult to access through physicians. Contradictory estimates are seen between the continuous MCA and Pardo scores when prescription opioid deaths are the outcome variable. The MCA score's estimates are positive, while the Pardo score shows negative coefficients. In Pardo's 2017 study, his coefficient estimates for his PDMP score variable were also negative, however, they were statistically significant. It is important to note that the majority of the continuous measures are not statistically significant in either the MCA- or Pardo-based fixed effects models for prescription opioid deaths, suggesting that increases in PDMP regulations have no association with the prescription opioid-related death rate.

Table 3.3. Fixed Effects Model Estimates using MCA Score of PDMP Strength

	Model I		Model II		Model III		Model IV	
	ln(Prescription Deaths)	ln(Heroin Deaths)	ln(Prescription Deaths)	ln(Heroin Deaths)	ln(Prescription Deaths)	ln(Heroin Deaths)	ln(Prescription Deaths)	ln(Heroin Deaths)
MCA Score (continuous)	0.001	0.004	0.004	0.013*				
MCA Score (class)								
1st quartile					-0.158*	-0.338*	-0.218**	-0.209
2nd quartile					-0.064	-0.300	-0.109	-0.196
3rd quartile					-0.083	-0.157	-0.110	-0.016
4th quartile					-0.057	-0.063	-0.078	0.066
Agency								
Law Enforcement			0.059	0.015			0.163	0.181
Department of Health			-0.162*	-0.544***			-0.035	-0.375**
Consumer Protection			0.082	-0.397			0.276***	-0.175
Professional and licensing			-0.036	-0.285*			0.081	-0.112
Other			0.034	-0.202			0.174	-0.061
Naloxone	0.021	0.347**	0.022	0.332**	0.002	0.306**	0.006	0.317**
Good Samaritan	0.112	0.280**	0.119	0.318**	0.132	0.326**	0.135	0.340***
Pain clinic laws	-0.038	0.499*	-0.049	0.457*	-0.047	0.473*	-0.058	0.451*
Medical marijuana dispensary	0.137	0.148	0.124	0.129	0.149	0.162	0.126	0.131
Education	0.037*	0.074**	0.037**	0.068**	0.034*	0.062*	0.036**	0.065**
White	0.029*	0.045	0.033*	0.057*	0.034**	0.059**	0.037**	0.064**
ln(Income)	0.929**	-2.189***	0.923**	-2.255***	-1.005***	-2.290***	-0.973***	-2.251***
State Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.730	0.687	0.733	0.702	0.733	0.696	0.736	0.702
N	918	918	918	918	918	918	918	918

*Note: *, **, and ** denote statistical significance at the 10%, 5%, and 1% levels, respectively*

Table 3.4. Fixed Effects Model Estimates using Pardo Score of PDMP Strength

		Model I		Model II		Model III		Model IV	
		ln(Prescription Deaths)	ln(Heroin Deaths)	ln(Prescription Deaths)	ln(Heroin Deaths)	ln(Prescription Deaths)	ln(Heroin Deaths)	ln(Prescription Deaths)	ln(Heroin Deaths)
Pardo Score (continuous)		-0.003	-0.002	-0.001	0.013				
Pardo Score (class)									
	1st quartile					-0.154*	-0.447**	-0.211**	-0.348**
	2nd quartile					-0.025	-0.100	-0.072	-0.022
	3rd quartile					-0.088	-0.039	-0.111	0.080
	4th quartile					-0.099	-0.068	-0.115	0.056
Agency									
	Law Enforcement			0.065	0.002			0.151	0.182
	Department of Health			-0.133	-0.525**			-0.030	-0.338*
	Consumer Protection			0.107	-0.387			0.271***	-0.060
	Professional and licensing			-0.010	-0.272			0.085	-0.081
	Other			0.015	-0.247			0.146	0.02
Naloxone		0.023	0.350**	0.027	0.339**	-0.007	0.261*	-0.001	0.276**
Good Samaritan		0.111	0.277**	0.113	0.312**	0.129	0.332***	0.128	0.343***
Pain clinic laws		-0.027	0.518*	-0.036	0.477*	-0.025	0.473*	-0.036	0.447*
Medical marijuana dispensary		0.145	0.160	0.135	0.146	0.153	0.184	0.134	0.152
Education		0.037*	0.075**	0.038**	0.071**	0.035*	0.064**	0.037**	0.067**
White		0.029*	0.044	0.032*	0.055*	0.032*	0.061**	0.035**	0.067**
ln(Income)		-0.910**	-2.157***	0.912**	-2.249***	-0.953**	-2.365***	0.931***	2.337***
State Effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.730	0.687	0.732	0.700	0.734	0.703	0.737	0.708
N		918	918	918	918	918	918	918	918

*Note: *, **, and ** denote statistical significance at the 10%, 5%, and 1% levels, respectively*

Table 3.5. Fixed Effects Model Estimates using ‘Prescribe’

	Model I		Model II	
	ln(Prescription Deaths)	ln(Heroin Deaths)	ln(Prescription Deaths)	ln(Heroin Deaths)
Prescribe (0/1)	0.247**	0.566***	0.263**	0.540***
Agency				
Law Enforcement			0.116	0.139
Department of Health			-0.119	-0.413**
Consumer Protection			0.121	-0.283
Professional and licensing			0.014	-0.146
Other			0.115	-0.068
Naloxone	0.029	0.366**	0.037	0.370***
Good Samaritan	0.081	0.207*	0.082	0.236**
Pain clinic laws	-0.079	0.411*	-0.086	0.401*
Medical marijuana dispensary	0.126	0.125	0.104	0.105
Education	0.033*	0.064*	0.034*	0.065**
White	0.030*	0.046*	0.032*	0.054*
ln(Income)	-0.864**	-2.036***	-0.815**	-2.020***
State Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
R^2	0.733	0.697	0.736	0.707
N	918	918	918	918

*Note: *, **, and ** denote statistical significance at the 10%, 5%, and 1% levels, respectively*

Moving to the PDMP scores that are broken down in quartiles for explanatory variables, there is a decreasing returns to scale effect which is similar to what was observed in Pardo's original study. Estimates show a statistically significant negative association with prescription and heroin-related overdose deaths for a majority of the first (lowest) quartile of scores using both the MCA- and Pardo-generated measures of PDMP strength. However, higher quartiles of scores do not indicate a statistically significant association with either heroin or prescription overdose deaths. These results indicate that states outside of the least stringent PDMP cohort have not seen any changes to their prescription or illicit opioid death rates.

Fixed Effects Models with Mandatory Prescriber Use Variable

The estimates for when the binary *Prescribe* variable is used as the measure of PDMP robustness are displayed in Table 3.5. All of the models show a positive and highly statistically coefficient estimate for Prescribe. Thus, a state's requirement that their physicians have to query the PDMP prior to writing opioid prescriptions is associated with increases in both prescription and illicit opioid death rates. These results are consistent with the findings of Faryer (2017) and Victor (2017) which saw an increase in heroin misuse after Kentucky's PDMP required mandatory use before dispensing opioid medications. However, they differ from the results seen in previous studies which show that obligatory physician access decreases prescription opioid misuse (Dowell et al., 2016; Ali et al., 2017; Grecu et al., 2019).

Discussion

This study looks at how PDMP robustness impacts both prescription and heroin overdose deaths across the U.S. during 1999 to 2016. A measure of PDMP strength is created by combining eleven different PDMP regulations using MCA, and by replicating a previously used score of PDMP vigor. Additionally, past studies and our MCA findings lead us to use a single variable denoting if physicians have to perform a PDMP search before writing prescriptions for controlled substances. This variable is used as a proxy for PDMP strength. Continuous measures of PDMP vigor mostly show no statistical impact on overdose deaths. When PDMP scores are broken into quartiles, only the lowest quartile of scores are seen to have a significant negative impact on overdose deaths – thus indicating a decreasing returns to scale effect. A possible explanation for this finding could be that states without substantial problems concerning prescription opioid and heroin misuse are not passing strict PDMP regulations. For the models using a simpler PDMP measure in the form of a binary variable for if physicians must access the PDMP before writing prescriptions, all estimates showed that having this particular regulation is associated with higher death rates for both prescription and illicit opioids.

Our findings generally align with previous works showing no significant association between PDMPs and lower incidences of prescription opioid misuse (Paulozzi et al., 2011; Brown et al., 2017). Our continuous measures of PDMP strength is not statistically associated with the prescription opioid-related death rate. Notably, our mandatory access indicator variable is found to be positively and significantly associated with the prescription-opioid related death rate (Table 5). This relationship is not intuitive considering that when physicians are directly surveyed, most report that having access to patient prescription histories through PDMPs lead them to prescribe fewer opioids (Rutkow, 2015; Lin et al., 2017). So, one would likely theorize that fewer prescribed opioids would in turn be associated with fewer incidences of deaths related to these substances. However, as Grecu (2019) points out, reduced prescription opioid prescriptions could have the unintentional consequence of driving black market prices up for these types of medications. These higher prices then incentivize persons to divert their legitimate prescriptions to illegal avenues which likely promotes the misuse of these substances. Focus groups with patients in substance abuse treatment programs in Wilmington, Delaware revealed that a primary source of illegally sold prescription opioids were from those who divert their medications for economic gains (Inciardi et al., 2009). Additionally, about a quarter of the 586 street drug users interviewed in New York City were found to use prescription opioids for medical purposes, while also diverting a share of their medications for resale (Davis and Johnson, 2008). Thus, it is evident from our findings that more research needs to be done into how PDMPs can effectively reduce prescription opioid diversion.

With respect to how PDMPs are associated with heroin misuse, one of our fixed effects models shows an instance where higher PDMP scores are associated with increased rates of heroin-related deaths. In other models, a strong positive association is observed between having a PDMP with mandatory access regulations and illicit overdose death rates – similar to what has been seen before in the literature (Faryer et al., 2017; Victor, 207). Interestingly, all the coefficient estimates for our mandatory access indicator variable are higher than those for the PDMP score variables. This result indicates that having that particular regulation in a state's PDMP is likely driving the association with illicit opioid deaths, since it has been shown that physicians access to PDMPs leads to them to prescribe fewer opioids (Rutkow, 2015; Lin et al., 2017). Therefore, it is reasonable that requiring physicians to use the PDMP is the most important predictor of higher incidences of illicit opioid deaths. This association would be due to the increased difficulty of obtaining prescription opioids, caused by physicians writing fewer prescriptions. In future works, researchers should further examine the theory that heroin can be a substitute for prescription opioids when these types of controlled substances become more difficult to procure due to government regulations for PDMPs.

Limitations to this study should also be considered. As previous studies have mentioned, there are a multitude of reasons for why deaths due to illicit opioids has risen recently. Some of the explanations are the rise of fentanyl mixed with heroin, and the low cost and widespread availability of heroin in comparison to prescription opioids (Mars et al., 2014; Frank and Pollack, 2017). These additional factors are not accounted for in our model, and have the potential to obscure the relationship between PDMP strength and overdose rates due to heroin – thus reducing our ability to make strong causal claims. Nonetheless, our results do offer some evidence of a positive relationship between PDMP robustness and illicit opioid deaths. This research area should continue to be explored as additional data becomes available.

CHAPTER IV

COMMUNITY MEETINGS ON THE RURAL OPIOID CRISIS: SETTING A PATH FORWARD BY LEARNING FROM OTHERS

Although the opioid epidemic has negatively impacted the entirety of the U.S. in recent years, rural areas have been especially affected. The Centers for Disease Control and Prevention (CDC) now estimates that the opioid death rate is higher in rural communities in comparison to urban ones (Mack, 2017). This difference is due to a variety of factors. Rural areas do not have extensive access to substance abuse treatment options, and are also faced with higher rates of opioid prescribing by physicians in comparison to urban areas (Rosenblatt et al., 2015; Hirchak and Murphy, 2017; Garcia et al., 2019). Additionally, the societal dynamics of rural communities may promote opioid misuse. There exists a stigma that surrounds receiving substance abuse treatment in a rural close-knit community, which discourages their utilization (Jackson and Shannon, 2012; Browne et al., 2016; Rigg et al., 2018). Those who live in rural locations also typically have wide social networks, which can expedite access to opioids (Keyes et al., 2014).

Similarly, administering services in rural communities to help with substance misuse can be burdensome. When substance abuse agencies in Washington state were surveyed about their practices, rural clinics noted that their small staff sizes prevented them from being able to devote work time to receive training on evidence-based practices (Dotson et al., 2014). Therapists noted that reliable transportation is a significant barrier for their rural clients who are receiving treatment for substance misuse, and this in turn makes it difficult for them to build a stable relationship with their patients (Godlaski and Clark, 2012). In focus groups, substance abuse counselors who work in rural areas stated that a lack of available funding makes having an adequate facility to provide services difficult (Pullen and Oser, 2014).

Despite these challenges, studies that have examined programs targeted at the opioid epidemic in rural areas have found promising results. Albert et al. (2011) focused on Project Lazarus, a community coalition in North Carolina aiming to help a county reduce their number of prescription opioid overdose deaths. Through outreach efforts such as prescriber education programs and providing naloxone[18] kits to at risk community members, they were successful in lowering the overdose death rate in their target area from 46.6 in 2009 to 29.0 in 2010. In Nevada, a training program where emergency medical technicians (EMTs) in rural communities learned how to effectively administer naloxone was found to increase their knowledge about the signs of an opioid overdose and decrease their concerns about using the product in the field (Zhang et al., 2018). Palombi et al. (2018) investigated a joint partnership between a pharmaceutical college and rural and indigenous citizens in northern Minnesota, which sought to increase community engagement by medical professionals. As a result of the cooperative effort, communities in the area have benefitted through forums, grants, and naloxone trainings designed to reduce overdose deaths.

This study takes a different look at the issue of administering programs to alleviate opioid misuse in rural communities. It describes a series of community meetings in a rural setting, where

[18] Naloxone is a medication that aids in reversing the effects of an opioid overdose.

community stakeholders learned about a variety of programs that can potentially help address the crisis. The ultimate goal of this study was for the participants to pinpoint where they would like future resources to go as they seek to reduce opioid misuse. Their decisions were based on the needs of the community, and the programs' respective feasibilities. Through involving the community, and hearing their input and views, these meetings laid the groundwork for stakeholders in the community to develop supported strategies in the future. To our knowledge, no previous studies have held and assessed meetings where multiple plans of action related to the opioid epidemic are examined, and where those who live in the community provided their input for which programs should be emphasized to reduce opioid misuse in their area. It is important to involve those from the area of interest in community-based research, as it has been shown to increase the knowledge of the community members which leads to better informed resource allocation and policy decisions (Israel et al., 1998; Macaulay et al., 1999; O'Brien and Whitaker, 2011).

Methods

Setting

This study occurred in the town of Ardmore, Oklahoma. The state of Oklahoma has been hit particularly hard by the opioid epidemic. According to the CDC, about 800 Oklahomans died due to drug overdoses in 2017, which is the twenty-eighth highest total number of deaths by state (Centers for Disease Control and Prevention, 2018). One potential explanation for why Oklahoma is experiencing a high number of drug-related deaths could be due to it being a predominately rural state (Keyes, 2014). According to the Economic Research Service Rural-Urban Continuum Codes, 59 of the 77 counties in Oklahoma are classified as non-metropolitan.

Of all the rural areas in Oklahoma, the community of Ardmore has been especially effected by the opioid epidemic. Ardmore is located in south central Oklahoma, with an estimated 2017

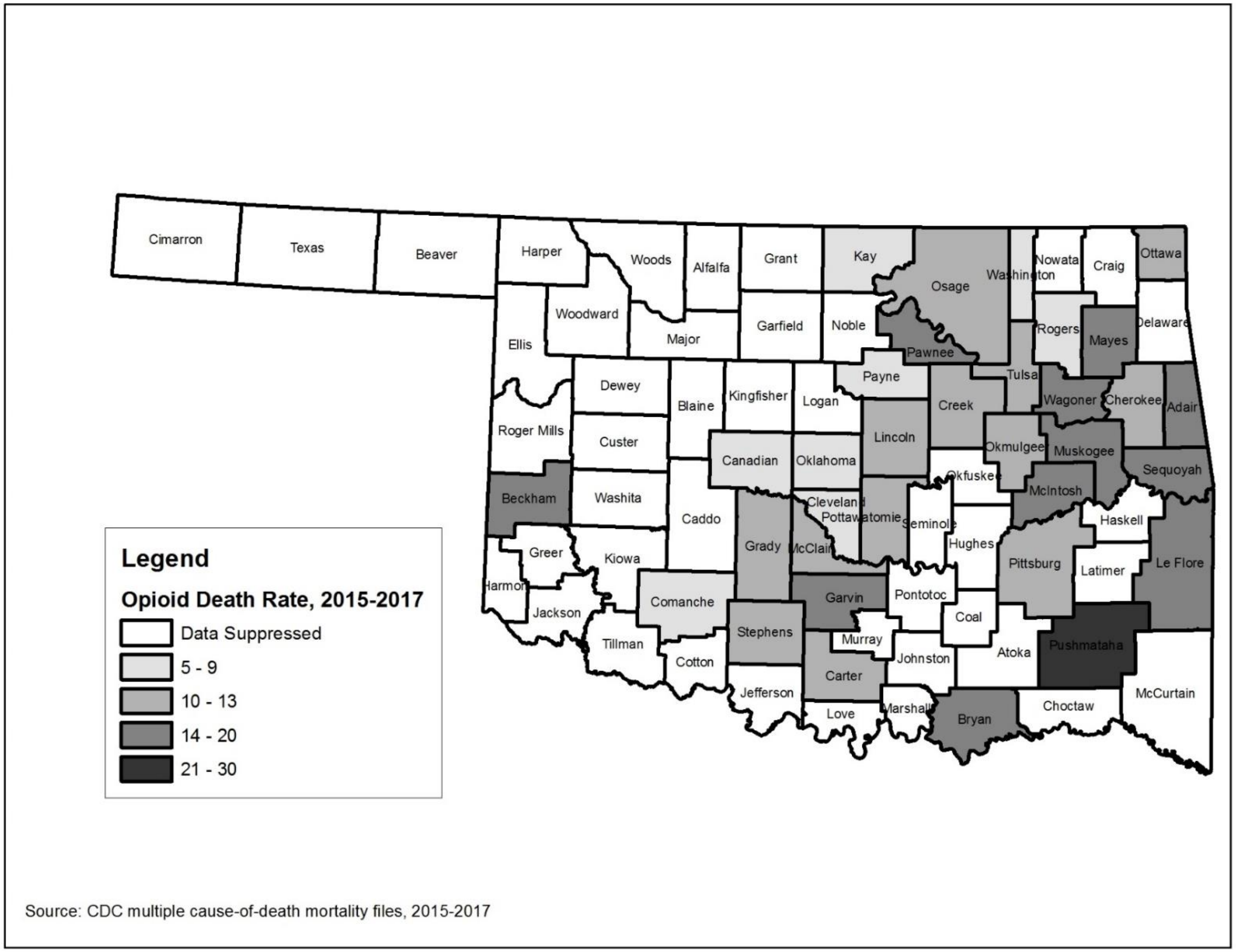


Figure 4.1. Oklahoma Age-adjusted Opioid-Related Death Rates, 2015-2017

population of about 25,000 residents (U.S. Census Bureau, 2019). Ardmore is also the county seat of Carter County, which is classified as non-metropolitan. Using CDC data, opioid-related deaths for 2015 through 2017 in Oklahoma counties are shown in Figure 4.1. Carter county has a death rate of about 13, which is slightly higher than both the U.S. and Oklahoma rates (12 and 11, respectively). As Figure 1 also shows, the surrounding counties (Garvin and Stephens) also have high opioid death rates for 2015 through 2017– thus implying that opioid misuse is an issue for the general area.

Participant Recruitment

Stakeholders who live or work in the Ardmore area were recruited primarily through word-of-mouth with the help of the researchers' professional contacts. A flyer was also created to be distributed throughout the community which explained the overall premise of the meetings, along with other pertinent information (Appendix 4.A). For the purposes of this research, stakeholders were considered to be those who were involved in organizations or jobs who worked on preventing or treating opioid misuse in the Ardmore area. For example, participants came from a nearby opioid treatment program, the Carter County sheriff's office, and a behavioral wellness center. All the organizations represented at the meetings are presented in Appendix 4.B.

Data Collection

All research procedures were approved prior to the meetings by a university human subjects institutional review board (IRB). A detailed agenda for the three meetings can be found in Appendix 4.C. Data collection occurred throughout the meetings, which were held two weeks apart from one another. During the first two meetings, four different categories of programs were introduced to the participants with the goal of providing information that could be used for group discussions and evaluations. The Ardmore area has current efforts in each of these four categories; however, participants' knowledge of the programs was assumed to be varied at the beginning of the meetings. To help explain the different categories of programs, professionals were brought in who have experience with these approaches and could speak to their strengths and weaknesses in helping to reduce opioid misuse. These professionals presented to the participants regarding the programs, and answered any questions participants had.

The four categories of programs that participants learned about are (A) programs that try to reduce the supply of opioids, (B) programs that try to reduce the demand for opioids, (C) opioid treatment options, and (D) overdose prevention and recovery programs. Examples for these categories of programs are listed in Table 4.1, along with the professional's organization who presented on each of the categories. For both (C) and (D), two speakers from different organizations spoke on each category. The first three categories (A, B, and C) came from a National Issues Forums guide regarding different strategies to address the opioid epidemic (Wharton, 2018). The last category (D) is included due to overdose prevention programs being proven in previous studies to be effective in reducing opioid-related deaths in rural areas (Albert et al., 2011; Zhang et al., 2018). A selection of pictures from the presentations are displayed in Appendix 4.D.

Surveys

The first method in which data was collected in this study was through two surveys. Meeting members were provided with written informed consent forms before they took the surveys, which stated that their participation was voluntary. Surveys were distributed at the beginning of the first meeting (the 'pre' survey), and at the end of the third meeting (the 'post' survey). The pre and post surveys are identical, and is displayed in Appendix 4.E. The rationale behind distributing surveys at the beginning and end of the meetings is to determine if participants' opinions changed as a result of the presentations and group discussions. To match the surveys among the two different time periods, participants provided a 4 digit ID at the start of their survey. To avoid

Table 4.1. Program Examples and Represented Presenter Organizations

Category	Examples	Organization of Presenter(s)
[A]: Programs that try to reduce the supply of opioids	Law enforcement efforts, prescribing guidelines for physicians, and legislative measure to try and reduce doctor shopping	Oklahoma Bureau of Narcotics and Dangerous Drugs
[B]: Programs that try to reduce the demand for opioids	Public health campaigns, youth intervention programs, and reduced marketing for opioids in the community	Wichita Mountains Prevention Network
[C]: Opioid treatment programs	Medication-assisted treatment (MAT), physician prescribing of buprenorphine, abstinence-based programs, and peer recovery support	Private practice physician and Southern Oklahoma Treatment Services
[D]: Overdose prevention and recovery	Making naloxone available to those in the community and providing education on how to administer naloxone safely	Ardmore Police Department and Oklahoma Department of Mental Health and Substance Abuse

participants forgetting their ID between the first and third meetings, the ID was comprised of the first and third letters of their first name and the day of the month they were born. Therefore, the unique nature of the number ensured that each participant would provide the same ID for the pre and post surveys.

Questions on the surveys included eliciting participant's opinions on issues related to the opioid epidemic, along with their level of familiarity for the four categories of programs discussed during the meetings. The next subset of questions asked the participants how effective they think each category's current efforts are in addressing the opioid epidemic in Ardmore, and if they believe more or less resources should be devoted to efforts in the category. Participants were also asked the percentage of total efforts (out of 100) they believe Ardmore currently puts into each category, and how much effort should be directed towards that category in the future. The last subgroup of questions asked about the participant's demographics, including their race, household income, highest education level received, political affiliation, age, gender, and how long they have lived in the Ardmore area.

Study Circles

The second data collection technique used in this study was study circles. Study circles are a tool for encouraging group discussion where participants are randomly broken into smaller groups (of 5 to 6 participants), given a list of questions to prompt dialogue, and then report as a group. A comparable study used study circles to address poverty in rural communities in Idaho (Cummins et al., 2012). Two study circles occurred during the community meetings, one at the second meeting and one at the third. The first study circle (at the second meeting) asked the groups why they believe opioid misuse is an issue for the area, and had them report back the top three reasons they came up with. Questions on the first study circle prompt also included asking the participants whether any of the categories of programs discussed directly address the underlying reasons for opioid misuse that they developed, and which reasons will be the easiest and hardest to address in the future. For the second study circle, groups were asked about the assets present in the Ardmore area that help each of the four categories of programs be effective. Groups were also asked what specific programs they believe should be expanded (and conversely, reduced) in the future, and reported back the programs they identified. The study circle guides distributed to participants are shown in Appendix 4.F.

Category Voting

To quantify how the participants felt resources should be directed to each of the four categories in the future, a voting exercise was conducted at the third community meeting. In this exercise, each participant was handed a strip of four different colored stickers and verbally given a hypothetical scenario. In this scenario, they had ten dollars to devote to the four categories of programs. Yellow stickers denoted four dollars, blue was for three dollars, green was for two dollars, and red was for one dollar. Participants had to decide how they wanted to allocate their ten dollars between the programs, and therefore choose which program they believe should receive the most (and least) resources. Each participant marked their final decision on a large sheet of paper in the meeting room which had the four categories listed and spaces for the stickers. This method provided a visual representation of how the meeting participants individually allotted their theoretical funds, which serves as a proxy for which program they believe should receive more resources in the future.

Results

Survey Results

Descriptive statistics for the meeting participants are displayed in Table 4.2. These descriptive statistics come from the surveys that were distributed at the first and third community meetings. 53 participants took the first survey (the ‘pre’ survey), with 32 participants taking the survey at

Table 4.2. Descriptive Statistics of Meeting Participants

	Aggregate		Matched
	Pre	Post	
Ethnicity			
White	75%	63%	72%
Non-White	25%	38%	28%
Yearly Household Income[a]			
Under $25,000	4%	9%	6%
$25,000 - $49,999	15%	9%	17%
$50,000 - $74,999	28%	38%	22%
$75,000 - $124,999	23%	28%	22%
$125,000 or more	13%	6%	22%
Education			
Did not graduate high school	0%	0%	0%
High school, GED, or Equivalent	6%	9%	6%
Some College / Associates Degree	19%	19%	11%
College Degree	43%	50%	50%
Post College Degree	30%	22%	33%
Gender			
Male	17%	25%	11%
Female	79%	75%	89%
Political Affiliation[a]			
Republican	34%	34%	33%
Democrat	30%	25%	33%
Independent	9%	19%	6%
Mean Age	42	42	38
Mean Number of Years Lived in Ardmore	21	19	18
Number of participants	53	32	18

[a] *The response categories included a 'Prefer Not to Answer' option*

the third community meeting (the ‘post’ survey). This group of 53 pre and 32 post responses makes up the aggregate sample in this study. It is important to note that the 32 participants at the third meeting were comprised of both participants who were present at the first meeting, and new participants. Between the pre and post survey, 18 participants were matched using the 4 digit ID they provided. The descriptive statistics that follow look at 2 distinct groups: the pre/post aggregate groups, and the matched group of 18.

Looking at the descriptive statistics, there is not a wide variation in demographics between the pre, post, and matched group. Most of the participants at the meetings were white, had household yearly incomes above $50,000, were college educated, female, and in their late 30’s to early 40’s. Among the groups, the participants had lived in the Ardmore area for an average of around 20 years, which means they have an extensive familiarity with the community. Political affiliation was split between Republican and Democrat, with only a small portion of the participants identifying as Independent.

Figure 4.2 shows the percentage of responses across varying categories to the statement ‘Like Alcoholism, Opioid Addiction Should be Treated as a Disease, Not a Crime’. Figure 2a is for the aggregate sample, with Figure 4.2b being for the matched sample of 18 participants. A majority of the participants’ responses in both the aggregate and matched samples, between the two time periods, strongly agreed or somewhat agreed with this statement. These responses fall in line with the American Medical Association, which classified addiction as a disease beginning in 1987 (Bettinardi-Angres and Angres, 2010). Most of the participants’ responses agreeing with this statement also indicates that they would lean towards providing those who are facing opioid misuse issues with treatment, instead of legal prosecution. Interestingly, for both the aggregate and matched samples, there was an increase seen in the “somewhat disagree” classification between the pre and post surveys. A possible justification for this finding is that a portion of the respondents during the meetings began to believe that legal prosecution is a more effective way to

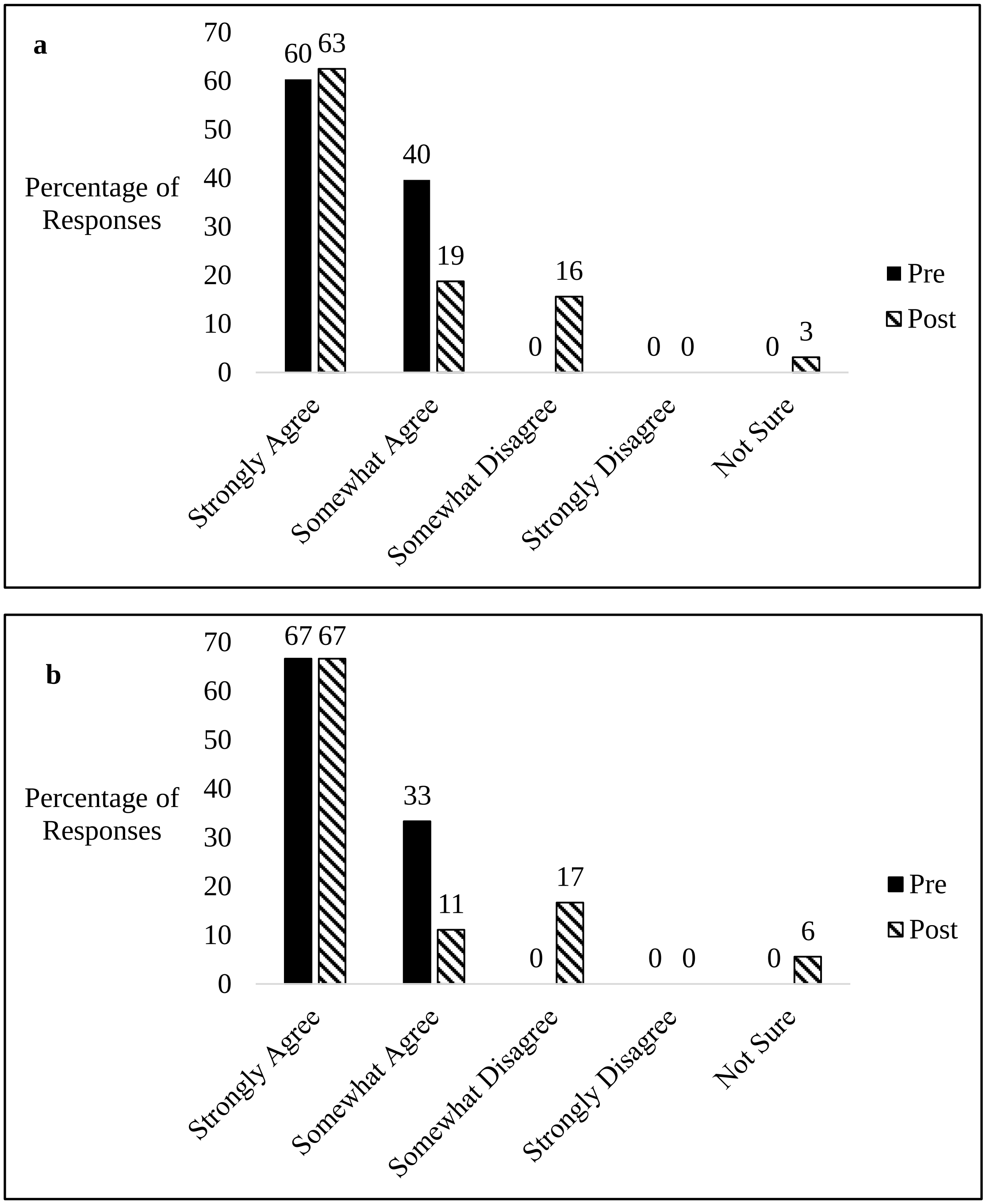


Figure 4.2. Percentage of Responses for the Statement: 'Like Alcoholism, Opioid Addiction Should be Treated as a Disease, Not a Crime' for (a) Aggregate Sample and (b) Matched Sample

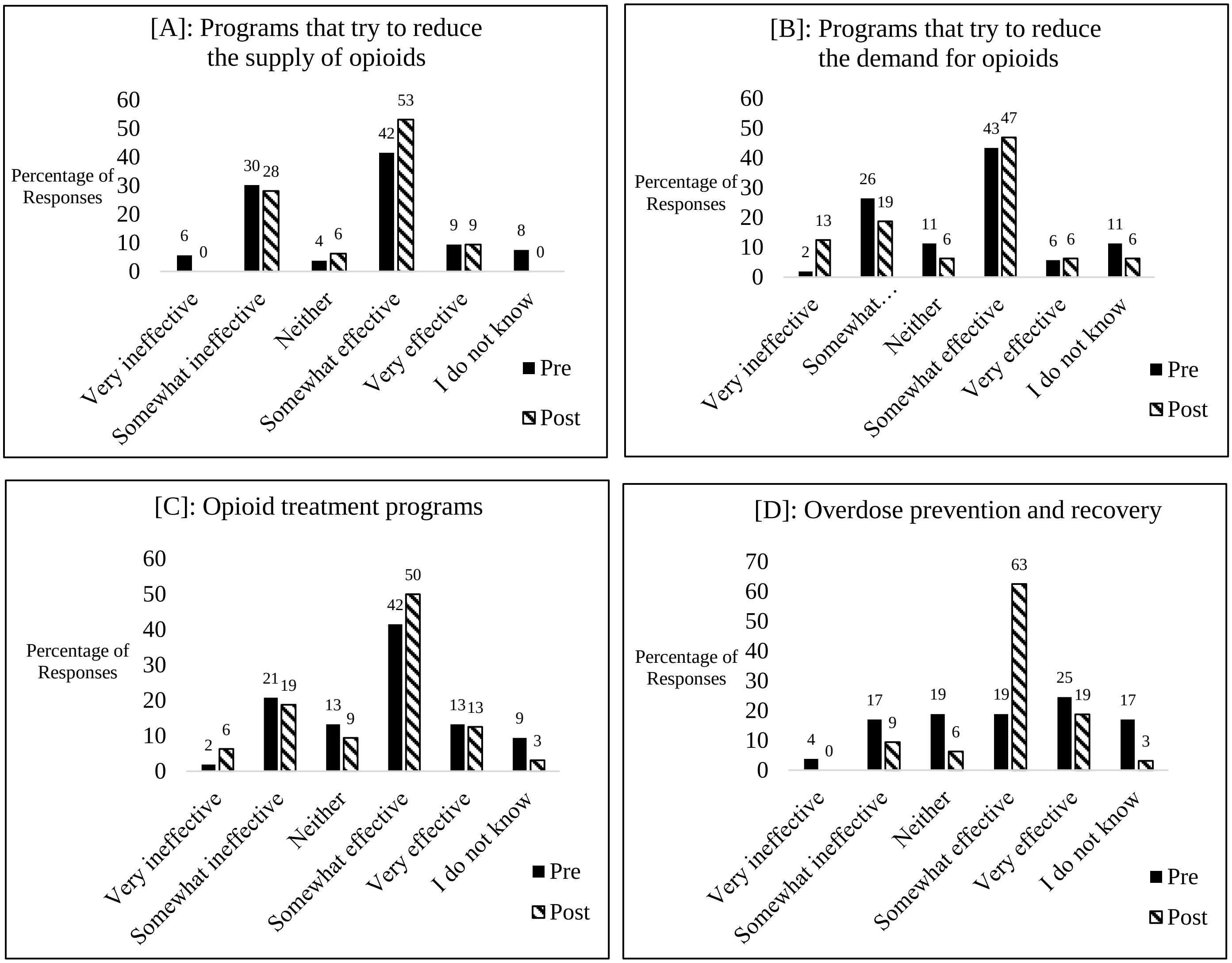


Figure 4.3. Percentage of Responses for How Effective These Efforts Currently are in Addressing the Opioid Epidemic in Ardmore, Aggregate Sample

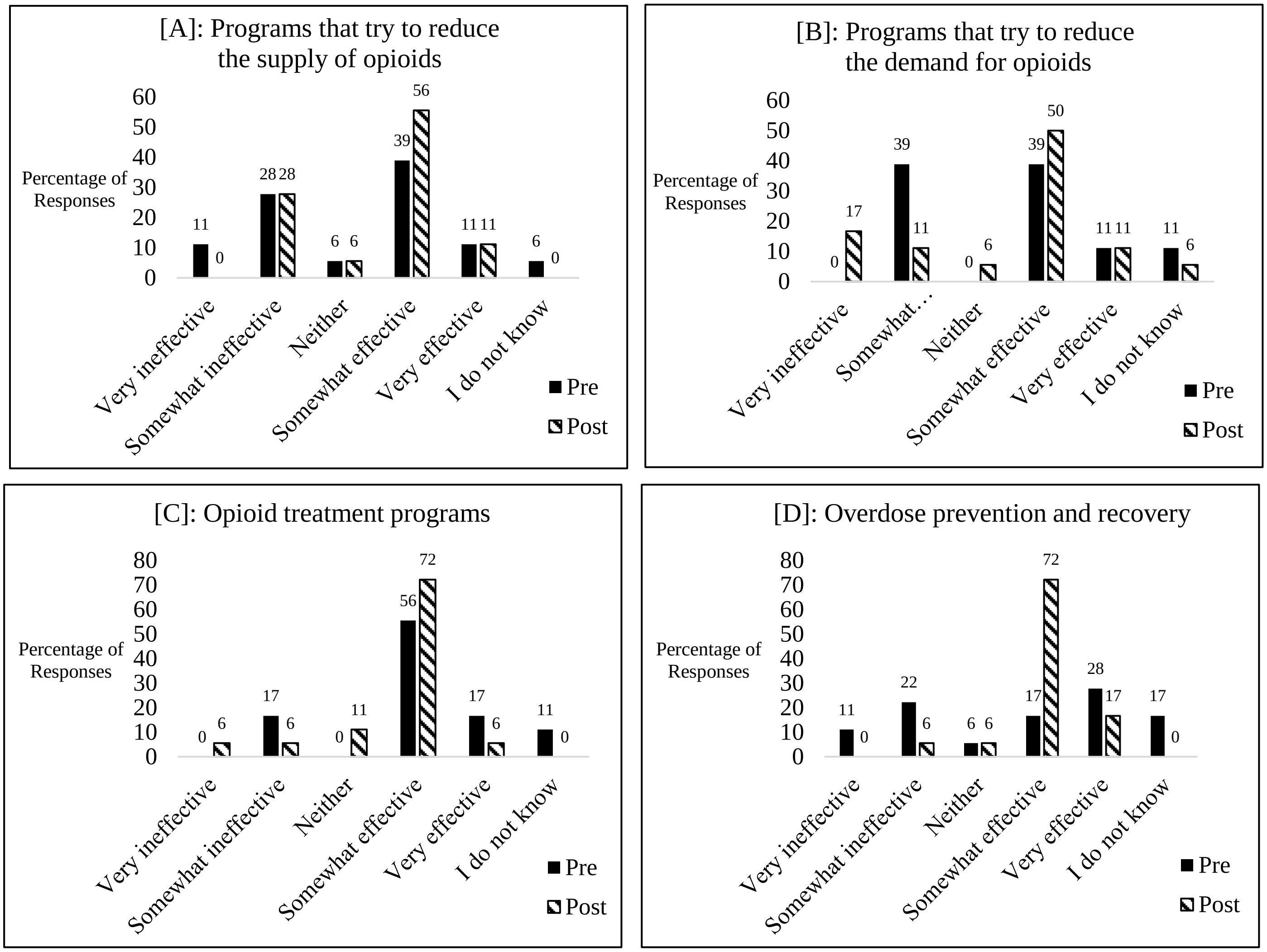


Figure 4.4. Percentage of Responses for How Effective These Efforts Currently are in Addressing the Opioid Epidemic in Ardmore, Matched Sample

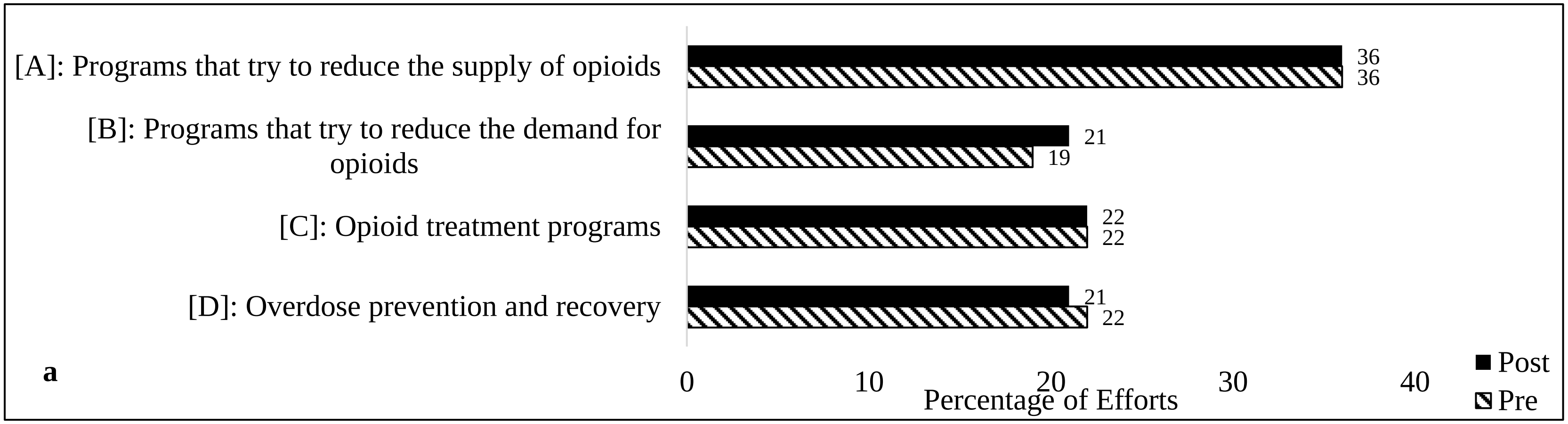
deter those from continuing substance use as opposed to offering rehabilitation to those experience an opioid addiction. During the first meeting, there was a discussion amongst the participants regarding Oklahoma State Question (SQ) 780 and 781 which went into effect in 2017. SQ 780 reclassified simple drug possession as a misdemeanor (as opposed to a felony) and SQ 781 made it possible for the savings from SQ 780 to be transferred into county government funds for substance abuse and mental health services (Oklahoma Policy Institute, 2018). Some of the participants felt that SQ 780 led to law enforcement having less authority and bargaining power when dealing with individuals charged with drug-related crimes, since misdemeanors are more minor than a felony. Thus, perhaps the participants who stated that they somewhat disagree with addiction being classified as a disease in the post survey were swayed by the conversation regarding SQ 780 and 781 into thinking that treating addiction as a felony is more effective in reducing misuse than classifying it as a misdemeanor.

Survey responses for questions asking the participants how effective they believe the four categories are in addressing the opioid epidemic in the Ardmore area are seen in Figures 4.3 and 4.4. Figure 4.3 is for the aggregate sample, with Figure 4.4 being for the matched sample. The "somewhat effective" option saw an increase in its percentage of responses between the pre and post surveys, for all four categories and with both the aggregate and matched samples. In the post survey period, a sizable portion of the responses indicated for all four categories of programs that they were somewhat effective in combatting the crisis in the community. This finding held for both the aggregate and matched samples. So, as a result of the group discussions and presentations, a considerable share of the participants still believe that current efforts in these categories are lacking in their efficacy, and still have room for improvement. Another notable finding from Figures 4.3 and 4.4 is that the percentage of responses in the "very ineffective" option for category B (programs that try to reduce the demand for opioids) saw a large increase between the pre and post period for both samples. For the aggregate sample, the option went from

2% to 13% of the responses, and for the matched sample it went from 0% to 17%. This result implies that at the end of the meetings, a portion of participants did not believe that present efforts focused on trying to reduce the demand for opioids in Ardmore are effective at all, which could be an area to direct efforts towards in the future. Or, it could suggest that this subset of participants do not believe that category B is useful at reducing opioid misuse in any capacity, and resources should be devoted to other types of programs.

Figure 4.5 shows the mean percentage of efforts (out of 100) that participants noted on their surveys that currently (Figure 4.5a) and should (Figure 4.5b) go in to each category for the aggregate sample. Figure 4.6 displays the same findings for the matched sample. Going from the pre to post periods, a majority of the means stayed the same. However, for the aggregate sample's responses for the percentage of efforts that Ardmore should put into each category (Figure 4.5b), noteworthy changes are seen for categories B (programs that try to reduce the demand for opioids) and D (overdose prevention and recovery). Participants thought less resources should go towards category B, and more resource should go towards category D moving from the pre to post periods. Another result worth mentioning is observed in Figure 4.6a, where the matched sample's percentage of efforts that they believe are currently in Ardmore increased for category C (treatment options) between the periods. This change is likely due to participants learning about different treatment options during the presentations and having discussion that allows them to hear other opinions.

For both the aggregate and matched samples, similar trends are observed. Participants believe that the most efforts in the Ardmore area are currently centered in category A (programs that try to reduce the supply of opioids). However, when asked how many efforts should go into each category, they indicate that category C (treatment options) should receive the most. This finding relates to a majority of survey responses either strongly or somewhat agreeing that addiction is



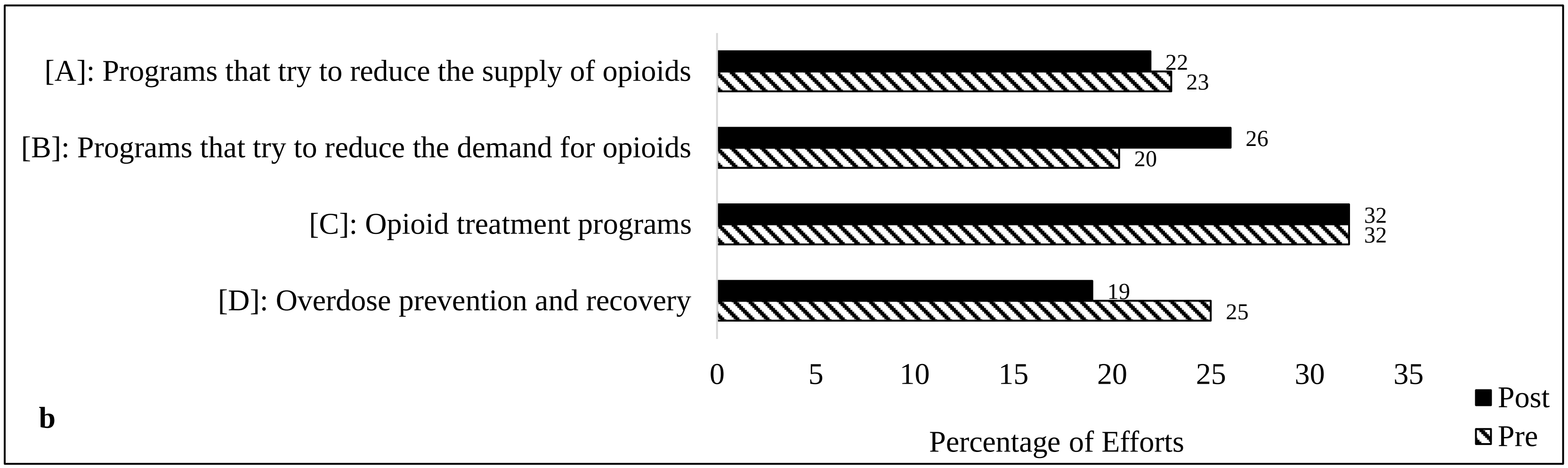


Figure 4.5. Mean Percentage of Efforts Ardmore (a) Currently Puts in to Each Category and (b) Should Put in to Each Category, Aggregate Sample

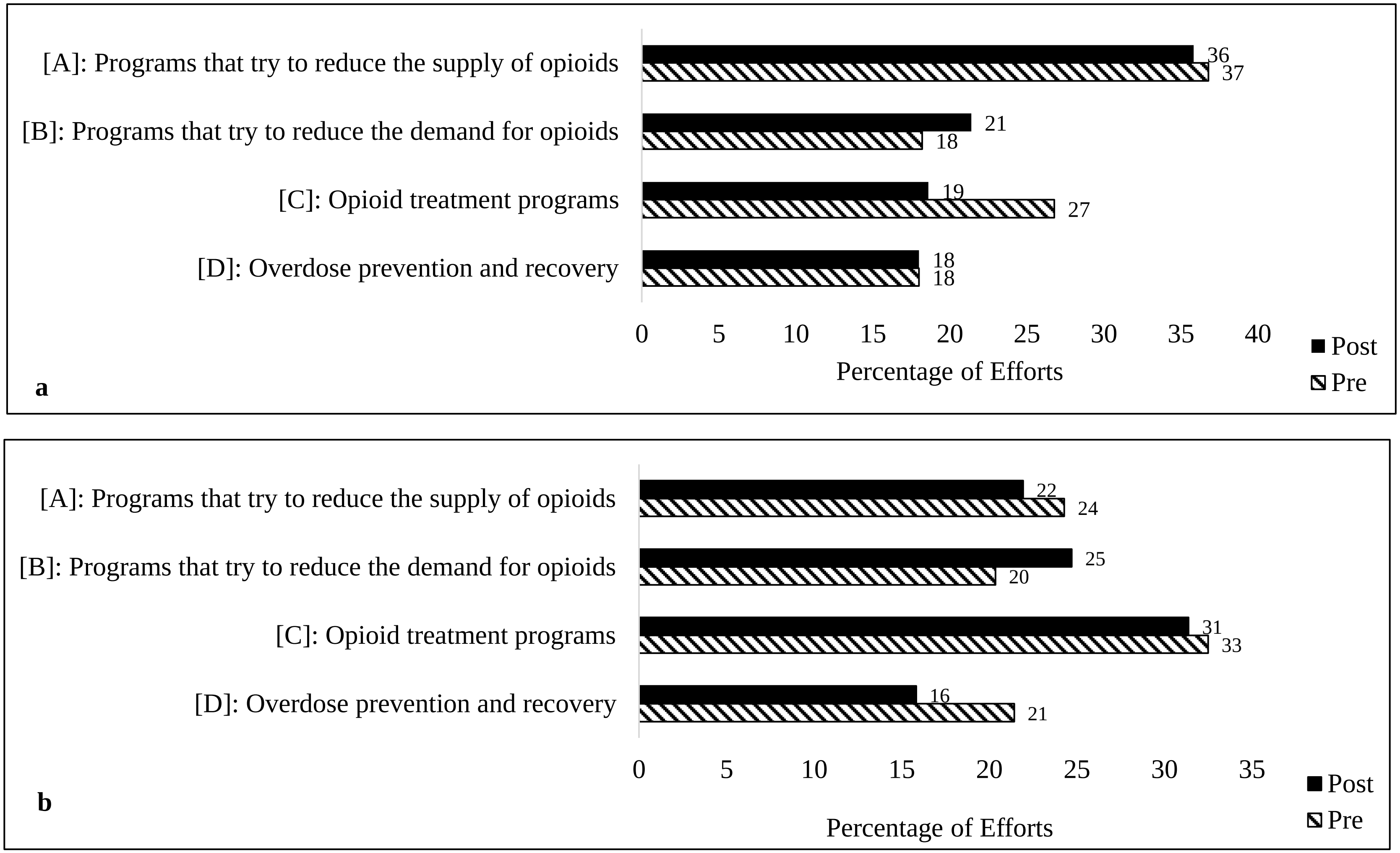


Figure 4.6. Mean Percentage of Efforts Ardmore (a) Currently Puts in to Each Category and (b) Should Put in to Each Category, Matched Sample

disease, not a crime (as seen in Figure 4.1). As a result, it is logical that treatment options for opioid misuse would be given the highest percentage of future efforts by participants.

Study Circle Results

The reasons for opioid misuse in the Ardmore community that groups identified in the first study circle are listed in Table 4.3. The most common reason was overprescribing by physicians, which has been identified as a significant contributor to the opioid crisis in previous research (Compton et al., 2015; Makary et al., 2017). Another reason was high incidences of adverse childhood experiences (ACE) in the community. ACEs consist of exposure to abuse and household dysfunction during ones childhood (Felitti et al., 1998). An individual's ACE score has been shown to be positively related to their likelihood of opioid misuse (Stein et al., 2018), so it is reasonable that participants would recognize this as a main reason for opioid misuse in their area.

Other reasons that the groups noted are societal factors such as social access and acceptability of opioids, which again have been identified as issues for rural areas (Young et al., 2012; Keyes et al., 2014). Some causes were particular to the Ardmore area. The location of Ardmore was recognized as being a contributing factor, since the community is situated off a major interstate highway (I-35) and between the major metropolitan areas of Oklahoma City and Dallas. Another reason was that a majority of the people in Ardmore are involved in working class jobs, which participants believe have a higher risk of injury than middle or upper class positions. Participants stated that those who become injured in the workplace are then prescribed opioids for pain management, which leads to misuse problems.

Table 4.4 shows the programs that the groups during the second study circle listed as being programs they would like to expand in the future. The most frequently cited program was youth education efforts that target school-age adolescents, which are a part of category B (programs that try to reduce the demand for opioids). The remaining programs cited by the study circle groups

Table 4.3. Study Circle 1 Findings, Reasons for Opioid Misuse in Ardmore area

Reason	Number of Times Reported by Groups
Overprescribing by physicians	5
High ACE scores	3
Social access / accessibility	3
Lack of entertainment / boredom	2
Lack of patient education	2
Location of area	2
High injury risk industries in area	2
Lack of treatment options	1
Prescription justification	1
Drug dealers and gangs	1

Table 4.4. Study Circle 2 Findings, Programs to be Expanded in the Future

Program	Number of Times Reported by Groups
Youth education programs in schools	4
Treatment for uninsured	2
MAT with buprenorphine	1
Inpatient services	1
Drug court	1

Table 4.5. Category Voting Findings, Dollar Allocation to Each Program

	Number of Allocated Stickers				
Program	Yellow ($4)	Blue ($3)	Green ($2)	Red ($1)	Total Dollar Amount
[C]: Opioid treatment programs	15	12	4	3	$107
[A]: Programs that try to reduce the supply of opioids	9	10	7	6	$86
[B]: Programs that try to reduce the demand for opioids	7	7	14	2	$79
[D]: Overdose prevention and recovery	1	3	7	22	$49

were a variety of different treatment options including providing treatment for uninsured persons, medication-assisted treatment (MAT) with buprenorphine, inpatient services, and drug courts.

Category Voting Results

Table 4.5 displays the findings for the participant voting exercise that occurred at the third meeting. Appendix 4.G also shows a picture of the paper where participants made their selections. In this exercise, participants had to denote with stickers how they would assign a hypothetical ten dollars, with each sticker representing a different dollar amount. Category C (opioid treatment options) received the most theoretical funding ($109) with categories A (programs that try to reduce the supply of opioids) and B (programs that try to reduce the demand for opioids) falling in second and third place, respectively. Category A obtained $86, while category B received $79. The small dollar difference ($7) between the two categories indicates that participants valued these programs to a similar degree.

The category of program that earned the least dollar allocation was category D (overdose prevention and recovery) with $49. A possible reason for this result in the voting exercise could be because after the presentations and discussions, participants believe current efforts in this category are sufficient and future resources should be directed elsewhere. Going back to the survey results seen in Figures 4.3 and 4.4, 82% of the responses in the aggregate sample and 89% of the responses in the matched sample believed that category D was either "somewhat effective" or "very effective" in addressing the opioid epidemic in Ardmore in the post period.

Discussion

This study is comprised of the findings from a series of three community meetings in Ardmore, Oklahoma. In these meetings, participants learned about four different categories of programs they can utilize to help with the high rates of opioid misuse in their area. The aim of these meetings was to use surveys, study circle discussions, and a voting exercise to determine participant perceptions of the opioid crisis, and how they believe resources should be allocated among the different programs in the future. Results reveal that the participants would like to direct resources mainly towards treatment services in their community. Participants would also like to expand efforts for youth education programs regarding opioids.

It is not surprising that participants believed that the most resources should go towards treatment options for those with opioid use disorders, as access to viable treatment is a problem for rural areas (Rosenblatt et al. 2015; Hirchak and Murphy, 2017). When prompted during the second study circle, participants listed that they would like to expand treatment for uninsured populations, inpatient services, and drug court programs. Another treatment option that was listed for future expansion was MAT with buprenorphine. In a MAT program with buprenorphine, patients have to visit the facility less frequently than if they were in a MAT program with methadone (Center for Substance Abuse Treatment, 2005). Patients can also receive the medication from their primary care physician, if the physician is trained and has the waiver to prescribe it (Substance Abuse and Mental Health Services Administration, 2019). Because of the features of a MAT program that uses buprenorphine, it has been identified as being a worthwhile treatment option for rural patients (Quest et al., 2012). Thus previous research and our study show that stakeholders in rural areas should look into expanding this form of treatment.

During the second study circle, it was also identified that youth education programs in schools should be expanded in the future. These programs fall under category B (programs that try to reduce the demand for opioids). Calling for the increase in programs targeting at adolescents in Ardmore is understandable, considering it has shown that rural drug users typically beginning their use at a younger age in comparison to their urban counterparts (Young et al., 2012). Research has shown that youth intervention programs are useful tools in decreasing opioid misuse in nonmetropolitan areas. Crowley et al. (2014) assessed the efficacy of school-based youth interventions in rural school districts in Iowa and Pennsylvania. Interventions began in sixth grade for the treated group, and researchers followed the adolescents in the study until they were in twelfth grade. They found that preventative programs were effective in reducing nonmedical prescription opioid misuse for the youths in their sample. Similar results are seen in Spoth et al. (2013) when they examined the effectiveness of family-focused and school-based youth intervention programs. Future research should continue to look into the effects of providing youth education programs to rural adolescents on later opioid misuse – and in particular what type of intervention works best.

Of special note in this study is the category of programs that did not receive a lot of funding in terms of the hypothetical voting exercise, category D. This category was for overdose prevention and recovery programs, and was allocated about half of the funds as category C (opioid treatment programs). When evaluating the survey responses, over 80% of the responses in the post survey deemed category D as being either “somewhat” or “very” effective in addressing opioid misuse in Ardmore for both the aggregate and matched samples. These findings could be attributed to Oklahoma currently being highly involved in taking measures to reduce fatal opioid overdoses. The Oklahoma Department of Mental Health and Substance Abuse Services is active in training citizens to use naloxone, and having it available across the state for free (Oklahoma Department of Mental Health and Substance Abuse Services, 2019). Additionally, Oklahoma passed a Good Samaritan law which went into effect in 2018 (Oklahoma State Legislature, 2018). Good Samaritan laws allow persons to report an overdose to authorities, without being prosecuted under certain circumstances. Another overdose prevention tool that Oklahoma is involved with is the Overdose Detection Mapping Application Program (ODMAP). First responders to an opioid overdose report the location of the incident, along with other information including victim details, the suspected drug used, and whether or not naloxone was used to ODMAP. Then, agencies can access this data to see if there are any overdose spikes occurring in their area, and take appropriate measures if necessary. Currently, 79 law enforcement agencies across the state of Oklahoma use ODMAP (Overdose Detection Mapping Application Program, 2019).

This study is not without its limitations. The findings from this research are specific to the Ardmore, Oklahoma community and the participants that partook in the meetings. Future researchers should expand on these meetings in their areas of interest, and determine if these results hold for other rural communities – which may face very different circumstances. Additionally, participants' opinions regarding the programs may have been swayed by the presenting skills of the experts, which varied across the categories. Participant perceptions about the cost of each category of program could have also influenced the voting exercise. Category C (opioid treatment programs) may have received the most funds due to the fact that these programs cost more to implement in the community in comparison to the other categories of programs. Another limitation is that although the categories of programs discussed in this study were broad in nature, they did not encompass every possible tool available to address the crisis. For example, the harm reduction strategy of a syringe exchange program was not discussed, and participants' views on this approach was not elicited through our data collection techniques. The use of syringe exchange programs has been shown to be associated with subsequent retention in substance use treatment (Hagan et al., 2000). Thus, future studies should look into whether or not rural community members are willing to direct resources towards providing this service in their areas.

Overall, this study has described a series of community meeting seeking to develop a consensus for moving forward to address the rural opioid crisis in rural communities. The results show that participants are generally interested in further developing treatment and youth-based prevention efforts in their area, due to the needs of the area. While specific to Ardmore, this process could be replicated by other rural communities struggling with the opioid epidemic. The presented programs and speakers would vary, but the process should allow stakeholders to come together and begin the process of taking steps forward in bettering the health and well-being of their communities.

CHAPTER V

CONCLUSION

The three studies included in this dissertation provide a thorough explanation of several issues related to the rural opioid crisis. The first and second studies econometrically evaluate specific strategies to address the crisis, while the third study is on an Extension-led community discussion on the best path forward. The first study (Chapter 2) looks at opioid treatment programs (OTPs) in the South census region that existed in 2013. Chapter 3 contains the second study, which focuses on prescription drug monitoring programs (PDMPs) from 1999 to 2016. The third study in Chapter 4 is an evaluation of a series of three community meetings that took place in Ardmore, Oklahoma. Moving forward, the findings of these studies can be used as an examination of the effectiveness of current approaches targeted at reducing the impacts of the crisis in rural areas. They can also guide future efforts.

Results show that OTPs in the South are not associated with reductions in opioid-related deaths in both the counties they are located in, and neighboring counties in the first study. This finding held for both metropolitan and non-metropolitan counties. Outside factors could be causing this lack of a negative relationship in rural areas, such as the cost of treatment, lack of access to OTPs, and transportation issues. Another potential issue is that rural OTPs could locate in places with high crime rates, which leads to increased incidences of opioid misuse. These issues concerning OTPs should be explored further.

The second study found that PDMP scores are generally not associated with prescription opioid-related deaths at the state level. For illicit opioid-related deaths, one model saw a positive relationship between PDMP score and the heroin death rate. This result lends some support to the hypothesis that stringent PDMPs lead to increases incidences of deaths attributed to illicit opioids. Models were also executed which used a binary variable indicating if the state's PDMP requires physicians to check the PDMP prior to writing prescriptions for controlled substance. This regulation was seen to have the highest coordinate score in the multiple correspondence analysis (MCA), which signals that is the most important regulation that makes up a state's overall PDMP score. When only the mandatory access binary variable was included in the fixed effects models, it was positively associated with both the illicit- and prescription-opioid related death rate. Future policy-makers looking to increase the efficacy of PDMPs should examine their possible unintended consequences on heroin deaths. They should also delve further into why the mandatory access provision in PDMPs is associated with higher prescription opioid-related deaths. A possible reasoning is that the regulation leads to more prescription opioid diversion, which leads to increased misuse.

Participants who attended the community meetings in Ardmore, Oklahoma demonstrated that they would like to devote future resources towards treatment options for those dealing with opioid use issues. They also noted that they would like to expand youth education programs in school, which would be targeting at preventing adolescent opioid misuse. Interestingly, participants chose to allocate the least amount of resources towards overdose prevention programs. This result could be due to Oklahoma being highly active in distributing naloxone, providing overdose prevention training, and tracking overdoses in communities. Because this study occurred in a select rural community, these meetings should be expanded to other areas to see if the results hold in different locations. This area of ripe for Extension intervention, and replication of these meetings would be an appropriate use of land-grant resources.

As this dissertation shows, the rural U.S. is in need of programs dedicated to reducing opioid misuse. The outcomes and conclusions from these three studies demonstrate that a diverse approach is needed to combat the opioid crisis in rural areas. Programs and policies should focus both on the prevention of further opioid misuse, and making treatment accessible for all populations. Additionally, researchers and policy-makers should continue community-based research, to explore the specific needs of rural areas in their efforts to combat the opioid crisis.

REFERENCES

Abdi, H., and D. Valentin. 2007. Multiple Correspondence Analysis. In Neil Salkind, ed. *Encyclopedia of Measurement and Statistics*. SAGE Publications Inc.

Albert, S., F.W. Brason, C.K. Sanford, N. Dasgupta, J. Graham, and B. Lovette. 2011. Project Lazarus: Community-Based Overdose Prevention in Rural North Carolina. *Pain Medicine* 12: 77-85.

Ali, M.M, W.N. Dowd, T. Clasen, R. Mutter, and S.P. Novak. 2017. Prescription Drug Monitoring Programs, Nonmedical Use of Prescription Drugs, and Heroin Use: Evidence from the National Survey on Drug Use and Health. *Addictive Behaviors* 69: 65-77.

Amiri, S., R. Lutz, M.E. Socias, M.G. McDonell, J.M. Roll, and O. Amram. 2018. Increased Distance was Associated with Lower Daily Attendance to an Opioid Treatment Program in Spokane County Washington. *Journal of Substance Abuse Treatment* 93: 26-30.

Anderson, R.N., and H.M. Rosenberg. 1998. Age Standardization of Death Rates: Implementation of the Year 2000 Standard. *National Vital Statistics Reports* 47(3): 1-20.

Andrilla, C.H.A., T.E. Moore, and D.G. Patterson. 2019. Overcoming Barriers to Prescribing Buprenorphine for the Treatment of Opioid Use Disorder: Recommendations from Rural Physicians. *The Journal of Rural Health* 35(1): 113-21.

Andrilla, C.H.A., C. Coulthard, and E. Larson. 2017. Barriers Rural Physicians Face Prescribing Buprenorphine for Opioid Use Disorder. *Annals of Family Medicine* 15(4): 359-62.

Anselin, L. 1995. Local Indicators of Spatial Association – LISA. *Geographical Analysis* 27(2): 93-115.

Bao, Y., Y. Pan, A. Taylor, S. Radakrishnan, F. Luo, H.A. Pincus, and B.R. Schackman. 2016. Prescription Drug Monitoring Programs are Associated with Sustained Reductions in Opioid Prescribing by Physicians. *Health Affairs* 35(6): 1045-51.

Beardsley, B.A., E.D. Wish, D.B. Fitzelle, K. O'Grady, and A.M. Arria. 2003. Distance Traveled to Outpatient Drug Treatment and Client Retention. *Journal of Substance Abuse Treatment* 25: 279-85.

Bettinardi-Angres, and D.H. Angres. 2010. Understanding the Disease of Addiction. *Journal of Nursing Regulation* 1(2): 31-7.

Blackwell, M., S. Iacus, G. King, and G. Porro. 2010. cem: Coarsened Exact Matching in Stata. *STATA Journal* 9:524-46.

Bohnert, A.S., M. Valenstein, M.J. Bair, D. Ganoczy, J.F. McCarthy, M.A. Ilgen, and F.C. Blow. 2011. Association Between Opioid Prescribing Patterns and Opioid Overdose-Related Deaths. *The Journal of the American Medical Association* 305(13): 1315-21.

Brady, J.E., H. Wunsch, C. DiMaggio, J. Giglio, and G. Li. 2014. Prescription Drug Monitoring and Dispensing of Prescription Opioids. *Public Health Reports* 129(2): 139-47.

Branham, D.K. 2018. Time-Series Analysis of the Impact of Prescription Drug Monitoring Programs on Heroin Treatment Admissions. *Substance Use & Misuse* 53(4): 694-701.

Brown, R., M.R. Riley, L. Ulrich, E.P. Kraly, P. Jenkins, N.L. Krupa, and A. Gadomski. 2017. Impact of New York Prescription Drug Monitoring Program, I-STOP, on Statewide Overdose Morbidity. *Drug and Alcohol Dependence* 178: 348-54.

Browne, T., M.A. Priester, S. Clone, A. Iachini, D. DeHart, and R. Hock. 2016. Barriers and Facilitators to Substance Use Treatment in the Rural South: A Qualitative Study. *The Journal of Rural Health* 32(1): 92-101.

Centers for Disease Control and Prevention. 2018a. Drug Overdose Death Data. Available at: https://www.cdc.gov/drugoverdose/data/statedeaths.html, last accessed August 1, 2018.

-------------. 2018b. U.S. Opioid Prescribing Rate Maps. Available at: https://www.cdc.gov/drugoverdose/maps/rxrate-maps.html, last accessed February 1, 2019.

Center for Substance Abuse Treatment. 2005. Medication-assisted Treatment for Opioid Addiction in Opioid Treatment Programs. Available at: https://www.ncbi.nlm.nih.gov/books/NBK64164/pdf/Bookshelf_NBK64164.pdf, last accessed October 10, 2018.

-------------. 2004. Clinical Guidelines for the Use of Buprenorphine in the Treatment of Opioid Addiction. Available at: https://www.naabt.org/documents/TIP40.pdf, last accessed March 10, 2019.

Compton, W.M., M. Boyle, and E. Wargo. 2015. Prescription Opioid Abuse: Problems and Responses. *Preventative Medicine* 80: 5-9.

Connery, H.S. 2015. Medication-Assisted Treatment of Opioid Use Disorder: Review of the Evidence and Future Directions. *Harvard Review of Psychiatry* 23(2): 63-75.

Cortinovis, I., V. Vella, and J. Ndiku. 1993. Construction of a Socio-Economic Index to Facilitate Analysis of Health Data in Developing Countries. *Social Science & Medicine* 36(8): 1087-97.

Crowley, D.M., D.E. Jones, D.L. Coffman, and M.T. Greenberg. 2014. Can We Build an Efficient Response to the Prescription Drug Abuse Epidemic? Assessing the Cost Effectiveness of Universal Prevention in the PROSPER Trial. *Preventive Medicine* 62: 71-7.

Cummins, M, B. Petty, L. Hansen, K. Hoffman, and G. Wittman. 2012. Expanding the Reach of Extension to Underserved Audiences Through Study Circles in Rural Idaho. *Journal of Extension* 50(4): 1-5.

Dasgupta, N., K. Creppage, A. Austin, C. Ringwalt, C. Sanford, and S.K. Proescholdbell. 2014. Observed Transition from Opioid Analgesic Deaths toward Heroin. *Drug and Alcohol Dependence* 145: 238-41.

Davis, W.R., and B.D. Johnson. 2008. Prescription Opioid Use, Misuse, and Diversion Among Street Drug Users in New York City. *Drug and Alcohol Dependence* 92(1-3): 267-76.

Delcher, C., A.C. Wagenaar, B.A. Goldberger, R.L. Cook, and M.M. Maldonado-Molina. 2015. Abrupt Decline in Oxycodone-Caused Mortality After Implementation of Florida's Prescription Drug Monitoring Program. *Drug and Alcohol Dependence* 150: 63-8.

Dick, A.W., R.L. Pacula, A.J. Gordon, M. Sorbero, R.M. Burns, D.L. Leslie, and B.D. Stein. 2014. Growth in Buprenorphine Waivers for Physicians Increased Potential Access to Opioid Agonist Treatment, 2002-11. *Health Affairs* 34(6): 1028-34.

Dotson, J.A.W., J.M. Roll, R.R. Packer, J.M. Lewis, S. McPherson, and D. Howell. 2014. Urban and Rural Utilization of Evidence-Based Practices for Substance Use and Mental Health Disparities. *The Journal of Rural Health* 30: 292-9.

Dowell, D., K. Zhang, R.K. Noonan, and J.M. Hockenberry. 2016. Mandatory Provider Review and Pain Clinic Laws Reduce the Amounts of Opioids Prescribed and Overdose Death Rates. *Health Affairs* 35(10): 1876-83.

Dunn, K.M., K.W. Saunders, C.M. Rutter, C.J. Banta-Green, J.O. Merrill, M.D. Sullivan, C.M. Weisner, M.J. Silverberg, C.I. Campbell, B.M. Psaty, and M. Von Korff. 2010. Opioid Prescriptions for Chronic Pain and Overdose. *Annals of Internal Medicine* 152: 85-92.

Edlund, M.J., D. Steffick, T. Hudson, K.M. Harris, and M. Sullivan. 2007. Risk Factors for Clinically Recognized Opioid Abuse and Dependence among Veterans Using Opioids for Chronic Non-Cancer Pain. *Pain* 129: 355-62.

Ezzrari, A., and P. Verme. 2012. A Multiple Correspondence Analysis Approach to the Measurement of Multidimensional Poverty in Morocco, 2001-2007. *World Bank, Policy Research Working Paper #6087*.

Faryar, K.A., C.L. Freeman, A.K. Persaud, S.P. Furmanek, B.E. Guinn, W.A. Mattingly, T.L. Wiemken, K.A. Buckner, and M.R. Huecker. 2017. The Effects of Kentucky's Comprehensive Opioid Legislation on Patients Presenting with Prescription Opioid or Heroin Abuse to One Urban Emergency Department. *The Journal of Emergency Medicine* 53(6): 805-14.

Finklea, K., L.N. Sacco, and E. Bagalman. 2014. Prescription Drug Monitoring Programs. Available at: https://www.everycrsreport.com/files/20140324_R42593_b5e6bc388e7be92c9a1be399db0878fa177c6941.pdf, last accessed February 10, 2019.

Food and Drug Administration. 2018. Information About Medication-assisted Treatment (MAT). Available at: https://www.fda.gov/Drugs/DrugSafety/InformationbyDrugClass, last accessed September 21, 2018.

Ford, G.S. 2018. Is Faster Better? Quantifying the Relationship Between Broadband Speed and Economic Growth. *Telecommunications Policy* 42(9): 766-77.

Frank, R.G., and H.A. Pollack. 2017. Addressing the Fentanyl Threat to Public Health. *The New England Journal of Medicine* 376(7): 605-7.

Fullerton, C.A., M. Kim, C.P. Thomas, D.R. Lyman, L.B. Montejano, R.H. Dougherty, A.S. Daniels, S.S. Ghose, and M.E. Delphin-Rittmon. 2014. Medication-assisted Treatment with Methadone: Assessing the Evidence. *Psychiatric Services* 65(2): 146-57.

Garcia, M.C., C.M. Heilig, S.H. Lee, M. Faul, G. Guy, M.F. Iademarco, K. Hempstead, D. Raymond, and J. Gray. 2019. Opioid Prescribing Rates in Nonmetropolitan and Metropolitan Counties Among Primary Care Providers Using an Electronic Health Record System – United States, 2014-2017. *Centers for Disease Control and Prevention Morbidity and Mortality Weekly Report* 68(2): 25-30.

Godlaski, T.M., and J.J. Clark. 2012. Implementation Issues in an Innovative Rural Substance Misuser Treatment Program. *Substance Use & Misuse* 47: 1439-50.

Grecu, A.M., D.M. Dave, and H. Saffer. 2019. Mandatory Access Prescription Drug Monitoring Programs and Prescription Drug Abuse. *Journal of Policy Analysis and Management* 38(1): 181-209.

Hagan, H., J.P. McGough, H. Thiede, S. Hopkins, J. Duchin, and E.R. Alexander. 2000. Reduced Injection Frequency and Increased Entry and Retention in Drug Treatment Associated with Needle-Exchange Participation in Seattle Drug Injectors. *Journal of Substance Abuse Treatment* 19: 247-52.

Hewlett, L. and D.P. Wemeling. 2013. Survey of Naloxone Legal Status in Opioid Overdose Prevention and Treatment. *Journal of Opioid Management* 9(5): 369-77.

Hill, M.O., and A.J.E. Smith. 1976. Principal Component Analysis of Taxonomic Data with Multi-State Discrete Characters. *Taxon* 25(2/3): 249-55.

Hirchak, K.A., and S.M. Murphy. 2017. Assessing Differences in the Availability of Opioid Addiction Therapy Options: Rural versus Urban and American Indian Reservation Versus Nonreservation. *The Journal of Rural Health* 33(1): 102-9.

Huang, B., M. Dignan, D. Han, and O. Johnson. 2009. Does Distance Matter? Distance to Mammography Facilities and Stage at Diagnosis of Breast Cancer in Kentucky. *The Journal of Rural Health* 25(4): 366-71.

Iacus, S.M., G. King, and G. Porro. 2011a. Causal Inference without Balance Checking: Coarsened Exact Matching. *Political Analysis* 20(1): 1-24.

-------------. 2011b. Multivariate Matching Methods that are Monotonic Imbalance Bounding. *Journal of the American Statistical Association* 106(493): 345-61.

Imbens, G.W., and J.M. Wooldridge. 2009. Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature* 47(1): 5-86.

Inciardi, J.A., H.L. Surratt, T.J. Cicero, and R.A. Beard. 2009. Prescription Opioid Abuse and Diversion in an Urban Community. *Pain Medicine* 10(3): 537-48.

Israel, B.A., A.J. Schulz, E.A. Parker, and A.B. Becker. Review of Community-Based Research: Assessing Partnership Approaches to Improve Public Health. *Annual Review of Public Health* 19: 173-202.

Jackson, A., and L. Shannon. 2012. Barriers to Receiving Substance Abuse Treatment Among Rural Pregnant Women in Kentucky. *Maternal and Child Health Journal* 16(9): 1762-70.

Jacobson, J.O. 2006. Do Drug Treatment Facilities Increase Clients' Exposure to Potential Neighborhood-level Triggers for Relapse? A Small-Area Assessment of a Large, Public Treatment System. *Journal of Urban Health* 83(2): 150-61.

Jones, C.M. 2013. Heroin Use and Heroin Use Risk Behaviors Among Nonmedical Users of Prescription Opioid Pain Relievers – United States, 2002-2004 and 2008-2010. *Drug and Alcohol Dependence* 132: 95-100.

Jones, E.B. 2018. Medication-Assisted Opioid Treatment Prescribers in Federally Qualified Health Centers: Capacity Lags in Rural Areas. *The Journal of Rural Health* 34(1): 14-22.

Jones, C.M., M. Campopiano, G. Baldwin, and E. McCance-Katz. 2015. National and State Treatment Need and Capacity for Opioid Agonist Medication-Assisted Treatment. *American Journal of Public Health* 105(8): 55-63.

Joynt, M., M.K. Train, B.W. Robbins, J.S. Halterman, E. Caiola, and R.J. Fortuna. 2013. The Impact of Neighborhood Socioeconomic Status and Race on the Prescribing of Opioids in Emergency Departments Throughout the United States. *Journal of General Internal Medicine* 28(12): 1604-10.

Kao, D., L.R. Torres, E.G. Guerrero, R.L. Mauldin, and P.S. Bordnick. 2014. Spatial Accessibility of Drug Treatment Facilities and the Effect on Locus of Control, Drug Use, and Service Use Among Heroin-Injecting Mexican American Men. *International Journal of Drug Policy* 25: 598-607.

Kampman, K., and M. Jarvis. 2015. American Society of Addiction Medicine (ASAM) National Practice Guideline for the Use of Medications in the Treatment of Addiction Involving Opioid Use. *Journal of Addiction Medicine* 9(5): 358-67.

Keyes, K.M., M. Cerda, J.E. Brady, J.R. Havens, and S. Galea. 2014. Understanding the Rural-Urban Differences in Nonmedical Prescription Opioid Use and Abuse in the United States. *American Journal of Public Health* 104(2): 52-9.

Kohn, J.L. 2012. What is Health? A Multiple Correspondence Health Index. *Eastern Economic Journal* 38: 223-50.

Kolenikov, S., and G. Angeles. 2009. Socioeconomic Status Measurement with Discrete Proxy Variables: Is Principal Component Analysis a Reliable Answer?. *Review of Income and Wealth* 55(1): 128-65.

Kolodny, A., D.T. Courtwright, C.S. Hwang, P. Kreiner, J.L. Eadie, T.W. Clark, and G.C. Alexander. 2015. The Prescription Opioid and Heroin Crisis: A Public Health Approach to an Epidemic of Addiction. *Annual Review of Public Health* 36: 559-74.

Kvamme, E., M. Catlin, C. Banta-Green, J. Roll, and R. Rosenblatt. 2013. Who Prescribes Buprenorphine for Rural Patients? The Impact of Specialty, Location and Practice Type in Washington State. *Journal of Substance Abuse Treatment* 44: 355-60.

Lanier, W.A., E.M. Johnson, R.T. Rolfs, M.D. Fiedrichs, and T.C. Grey. 2012. Risk Factors for Prescription Opioid-Related Death, Utah 2008-2009. *Pain Medicine* 13: 1580-89.

Lankenau, S.E., M. Teti, K. Silva, J.J. Bloom, A. Harocopos, and M. Treese. 2012. Initiation into Prescription Opioid Misuse Among Young Injection Drug Users. *International Journal of Drug Policy* 23: 37-44.

Lin, D.H., E. Lucas, I.B. Murimi, K. Jackson, M. Baier, S. Frattaroli, A.C. Gielen, P. Moyo, L. Simoni-Wastila, and G.C. Alexander. 2017. Physician Attitudes and Experiences with Maryland's Prescription Drug Monitoring Program. *Addiction* 112(2): 311-9.

Loughnan, M.E., N. Nicholls, and N.J. Tapper. 2008. Demographic, Seasonal, and Spatial Differences in Acute Myocardial Infarction Admissions to Hospital in Melbourne Australia. *International Journal of Health Geographics* 7(42): 1-15.

Macaulay, A.C., L.E. Commanda, W.L. Freeman, N. Gibson, M.L. McCabe, C.M. Robbins, and P.L. Twohig. 1999. Participatory Research Maximises Community and Lay Involvement. *The BMJ* 319: 774-777.

Mack, K., C.M. Jones, and M.F. Ballesteros. 2017. Illicit Drug Use, Illicit Drug Use Disorder, and Drug Overdose Deaths in Metropolitan and Nonmetropolitan Areas – United States. *Centers for Disease Control and Prevention Morbidity and Mortality Weekly Report* 66(19): 1-12.

Makary, M.A., H.N. Overton, and P. Wang. 2017. Overprescribing is Major Contributor to Opioid Crisis. *The BMJ* 359: 1-2.

Mars, S.G., P. Bourgois, G. Karandinos, F. Montero, and D. Ciccarone. 2014. Every 'Never' I Ever Said Came True": Transitions from Opioid Pills to Heroin Injecting. *International Journal of Drug Policy* 25(2): 257-66.

Martinson, R. 1974. What Works? – Questions and Answers About Prison Reform. *The Public Interest* 35: 22-54.

Maxwell, J.C. 2011. The Prescription Drug Epidemic in the United States: A Perfect Storm. *Drug and Alcohol Review* 30: 264-70.

Maxwell, J.C. 2015. The Pain Reliever and Heroin Epidemic in the United States: Shifting Winds in the Perfect Storm. *Journal of Addictive Diseases* 34: 127-40.

Miller, M., C.W. Barber, S. Leatherman, J. Fonda, J.A. Hermos, K. Cho, and D.R. Gagnon. 2015. Prescription Opioid Duration of Action and the Risk of Unintentional Overdose Among Patients Receiving Opioid Therapy. *The Journal of the American Medical Association Internal Medicine* 175(4): 608-15.

Moody, L., E. Satterwhite, and W.K. Bickel. 2017. Substance Use in Rural Central Appalachia: Current Status and Treatment Considerations. *Journal of Rural Mental Health* 41(2): 123-35.

Monnat, S.M., and K.K. Rigg. 2016. Examining Rural/Urban Differences in Prescription Opioid Misuse Among US Adolescents. *The Journal of Rural Health* 32(2): 2014-18.

Muhuri, P.K., J.C. Gfroerer, and M.C. Davies. 2013. Associations of Nonmedical Pain Reliever Use and Initiation of Heroin Use in the United States. *Center for Behavioral Health Statistics Quarterly.*

National Institute on Drug Abuse. 2018. Principles of drug addiction treatment: A research based guide (Third Edition). Available at: https://d14rmgtrwzf5a.cloudfront.net/sites/default/files/675-principles-of-drug-addiction-treatment-a-research-based-guide-third-edition.pdf, last accessed July 10, 2018.

O'Brien, M.J., and R.C. Whitaker. 2011. The Role of Community-Based Participatory Research to Inform Local Health Policy: A Case Study. *Journal of General Internal Medicine* 26(12): 1498-1501.

Okie, S. 2010. A Flood of Opioids, a Rising Tide of Deaths. *The New England Journal of Medicine* 363(21): 1981-5.

Oklahoma Department of Mental Health and Substance Abuse Services. 2019. Opioid Overdose. Available at: http://okimready.org/overdose/, last accessed March 15, 2019.

Oklahoma Policy Institute. 2018. SQ 780 and SQ 781. Available at: https://okpolicy.org/sq-780-sq-781/, last accessed March 17, 2019.

Oklahoma State Legislature. 2018. Bill Information for SB 1367. Available at: http://www.oklegislature.gov/, last accessed March 17, 2019.

Oser, C.B., and K.L.H. Harp. 2015. Treatment Outcomes for Prescription Drug Misusers: The Negative Effect of Geographic Discordance. *Journal of Substance Abuse Treatment* 48: 77-84.

Overdose Detection Mapping Application Program. 2019. Participating Agencies. Available at: http://www.odmap.org/#agency, last accessed March 17, 2019.

Palombi, L.C., A. LaRue, and K.K. Fierke. 2018. Facilitating Community Partnerships to Reduce Opioid Overdose: An Engaged Department Initiative. *Research in Social and Administrative Pharmacy* In press.

Pardo, B. 2017. Do More Robust Prescription Drug Monitoring Programs Reduce Prescription Opioid Overdose? *Addiction* 112(10): 1773-83.

Patrick, S.W., C.E. Fry, T.F. Jones, and M.B. Buntin. 2016. Implementation of Prescription Drug Monitoring Programs Associated with Reductions in Opioid-Related Death Rates. *Health Affairs* 35(7): 1324-32.

Paulozzi, L.J., Kilbourne, E.M., and H.A. Desai. 2011. Prescription Drug Monitoring Programs and Death Rates from Drug Overdose. *Pain Medicine* 12: 747-54.

Paulozzi, L.J., and Y. Xi. 2008. Recent Changes in Drug Poisoning Mortality in the United States by Urban-Rural Status and by Drug Type. *Pharmacoepidemiology and Drug Safety* 17: 997-1005.

Peirce, G.L., M.J. Smith, M.A. Abate, and J. Halverson. 2012. Doctor and Pharmacy Shopping for Controlled Substances. *Medical Care* 50(6): 494-500.

Pollini, R.A., C.J. Banta-Green, J. Cuevas-Mota, M. Metzner, E. Teshale, and R.S. Garfein. 2011. Problematic Use of Prescription-Type Opioids Prior to Heroin Use Among Young Heroin Injectors. *Substance Abuse and Rehabilitation* 2: 173-80.

Powell, D., R.L. Pacula, and M. Jacobson. 2018. Do Medical Marijuana Laws Reduce Addictions and Deaths Related to Pain Killers? *Journal of Health Economics* 58: 29-42.

Pullen, E., and C. Oser. 2014. Barriers to Substance Abuse Treatment in Rural and Urban Communities: Counselor Perspectives. *Substance Use & Misuse* 49: 891-901.

Quest, T.L., J.O. Merrill, J. Roll, A.J. Saxon, and R.A. Rosenblatt. 2012. Buprenorphine Therapy for Opioid Addiction in Rural Washington: The Experience of the Early Adopters. *Journal of Opioid Management* 8(1): 29-38.

Rasubala, L., L. Pernapati, X. Valasquez, J. Burk, and Y.F. Ren. 2015. Impact of a Mandatory Prescription Drug Monitoring Program on Prescription of Opioid Analgesics by Dentists. *PLoS One* 10(8): 1-10.

Reifler, L.M., D. Droz, J.E. Bailey, S.H. Schnoll, R. Fant, R.C. Dart, and B.B. Bartelson. 2012. Do Prescription Monitoring Programs Impact State Trends in Opioid Abuse/Misuse? *Pain Medicine* 13: 434-42.

Reisman, R.M., P.J. Shenoy, A.J. Atherly, and C.R. Flowers. 2009. Prescription Opioid Usage and Abuse Relationships: An Evaluation of State Prescription Drug Monitoring Programs. *Substance Abuse: Research and Treatment* 3: 41-51.

Rigg, K.K., S.M. Monnat, and M.N. Chavez. 2018. Opioid-related Mortality in Rural America: Geographic Heterogeneity and Intervention Strategies. *International Journal of Drug Policy* 57: 119-29.

Robert Wood Johnson Foundation. 2018. Life in Rural America. Available at: https://www.rwjf.org/content/dam/farm/reports/surveys_and_polls/2018/rwjf449263, last accessed October 15, 2018.

Rosenblatt, R.A., C.H.A. Andrilla, M. Catlin, and E.H. Larson. 2015. Geographic and Specialty Distribution of US Physicians Trained to Treat Opioid Disorder. *Annals of Family Medicine* 13(1): 23-6.

Rosenblum, A., C.M. Cleland, C. Fong, D.J. Kayman, B. Tempalski, and M. Parrino. 2011. Distance Traveled and Cross-State Commuting to Opioid Treatment Programs in the United States. *Journal of Environmental and Public Health* 2011: 1-10.

Rutkow, L., L. Turner, E. Lucas, C. Hwang, and G.C. Alexander. 2015. Most Primary Care Physicians are Aware of Prescription Drug Monitoring Programs, But Many Find the Data Difficult to Access. *Health Affairs* 34(3): 484-92.

Seplaki, C.L., E.M. Agree, C.O. Weiss, S.L. Szanton, K. Bandeen-Roche, and L.P. Fried. 2013. Assistive Devices in Context: Cross-Sectional Association Between Challenges in the Home Environment and Use of Assistive Devices for Mobility. *The Gerontologist* 54(4): 651-60.

Schwartz, R.P., J. Gryczynski, K.E. O'Grady, J.M. Sharfstein, G. Warren, Y. Olsen, S.G. Mitchell, and J.H. Jaffe. 2013. Opioid Agonist Treatments and Heroin Overdose Deaths in Baltimore, Maryland, 1995-2009. *American Journal of Public Health* 103(4): 917-22.

Siegler, A., E. Tuazon, D.B. O'Brien, and D. Paone. 2014. Unintentional Opioid Overdose Deaths in New York City, 2005-2011: A Place-Based Approach to Reduce Risk. *International Journal of Drug Policy* 25: 569-74.

Skinner, A.C., and R.T. Slifkin. 2007. Rural/Urban Differences in Barriers to and Burden of Care for Children with Special Health Care Needs. *The Journal of Rural Health* 23(2): 150-7.

Spoth, R., L. Trudeau, C. Shin, E. Ralston, C. Redmond, M. Greenberg, and M. Feinberg. 2013. Longitudinal Effects of Universal Prevention Intervention on Prescription Drug Misuse: Three Randomized Control Trials with Late Adolescents and Young Adults. *Research and Practice* 103(4): 665-72.

Sourial, N., C. Wolfson, B. Zhu, J. Quail, J. Fletcher, S. Karunananthan, K. Bandeen-Roche, F. Beland, and H. Bergman. 2010. Correspondence Analysis is a Useful Tool to Uncover the Relationships Among Categorical Variables. *Journal of Clinical Epidemiology* 63: 638-46.

Sridharan, S., H. Tunstall, R. Lawder, and R. Mitchell. An Exploratory Spatial Data Analysis Approach to Understanding the Relationship Between Deprivation and Mortality in Scotland. *Social Science & Medicine* 65: 1942-52.

St. Louis County Prescription Drug Monitoring Program. 2019. PDMP Overview. Available at: https://www.stlouisco.com/Health-and-Wellness/PDMP, last accessed: March 1, 2019.

Stahler, G.J., S. Mazzella, J. Mennis, S. Chakravorty, G. Rengert, and R. Spiga. 2007. The Effect of Individual, Program, and Neighborhood Variables on Continuity of Treatment Among Dually Diagnosed Individuals. *Drug and Alcohol Dependence* 87: 54-62.

Stein B.D., R.L. Pacula, A.J. Gordon, R.M. Burns, D.L. Leslie, M.J. Sorbero, S. Bauhoff, T.W. Mandell, and A.W. Dick. 2015. Where is Buprenorphine Dispensed to Treat Opioid Use Disorders? The Role of Private Offices, Opioid Treatment Programs, and Substance Abuse Treatment Facilities in Urban and Rural Counties. *The Milbank Quarterly* 93(3): 561-83.

Stein, M.D., M.T. Conti, S. Kenney, B.J. Anderson, J.N. Flori, M.M. Risi, and G.L. Bailey. 2018. Adverse Childhood Experiences Effects on Opioid Use Initiation, Injection Drug Use, and Overdose Among Persons with Opioid Use Disorder. *Drug and Alcohol Dependence* 179: 325-9.

Stephens, J.M., S. Brotherton, S.C. Dunning, L.C. Emerson, D.T. Gilberston, D.J. Harrison, J.J. Kochevar, A.C. McClellan, W.M. McClellan, S. Wan, and M. Gitlin. 2013. Geographic Disparities in Patient Travel for Dialysis in the United States. *The Journal of Rural Health* 29(4): 339-48.

Substance Abuse and Mental Health Services Administration. 2019. Buprenorphine Waiver Management. *Substance Abuse and Mental Health Services Administration.* Available at: https://www.samhsa.gov/medication-assisted-treatment, last accessed March 18, 2019.

United States Census Bureau. 2019. QuickFacts Ardmore city, Oklahoma. Available at: https://www.census.gov/quickfacts/fact/table/ardmorecityoklahoma,US/PST045218, last accessed March 20, 2019.

Victor, G.A., R. Walker, J. Cole, and T.K. Logan. 2017. Opioid Analgesics and Heroin: Examining Drug Misuse Trends Among a Sample of Drug Treatment Clients in Kentucky. *International Journal of Drug Policy* 46: 1-6.

Visconti, A.J., G.M. Santos, N.P. Lemos, C. Burke, and P.O. Coffin. 2015. Opioid Overdose Deaths in the City and County of San Francisco: Prevalence, Distribution, and Disparities. *Journal of Urban Health* 92(4): 758-72.

Volkow, N.D., T.R. Frieden, P.S. Hyde, and S.S. Cha. 2014. Medication Assisted Therapies – Tackling the Opioid Epidemic. *New England Journal of Medicine* 370(22): 2063-6.

Wen, H., B.R. Schackman, B. Aden, and Y. Bao. 2017. States with Prescription Drug Monitoring Mandates Saw Reduction in Opioids Prescribed to Medicaid Enrollees. *Health Affairs* 36(4): 733-41.

Wharton, T. 2018. What Should We Do About the Opioid Epidemic?. Available at: https://www.nifi.com, last accessed March 18, 2019.

Whitacre, B., R. Gallardo, and S. Strover. 2014. Broadband's Contribution to Economic Growth in Rural Areas: Moving Towards a Causal Relationship. *Telecommunications Policy* 38(11): 1011-23.

Winstanley, E.L., Y. Zhang, R. Mashni, S. Schnee, J. Penm, J. Boone, C. McNamee, and N.J. MacKinnon. 2018. Mandatory Review of a Prescription Drug Monitoring Program and Impact on Opioid and Benzodiazepine Dispensing. *Drug and Alcohol Dependence* 188: 169-74.

Young, A.M., J.R. Havens, and C.G. Leukefeld. 2012. A Comparison of Rural and Urban Nonmedical Prescription Opioid Users' Lifetime and Recent Drug Use. *The American Journal of Drug and Alcohol Abuse* 38(3): 220-7.

Zaller, N., M., McKenzie, P.D. Friedmann, T.C. Green, S. McGowan, and J.D. Rich. 2013. Initiation of Buprenorphine During Incarceration and Retention in Treatment Upon Release. *Journal of Substance Abuse Treatment* 45(2): 222-6.

Zhang, X., C. Marchand, B. Sullivan, E.M. Klass, and K.D. Wagner. 2018. Naloxone Access for Emergency Medical Technicians: An Evaluation of a Training Program in Rural Communities. *Addictive Behaviors* 86: 79-85.

APPENDICES

Appendix 2.A. L1 Imbalance Measures for Metropolitan Counties

	Treatment 1: OTP in County before 2013		Treatment 2: OTP in Neighboring County before 2013	
	Unmatched Data	Matched Data	Unmatched Data	Matched Data
Age Adjusted Death Rates (2011-2013)	0.15	0.18	0.16	0.03
Prescription rate	0.12	0.27	0.23	0.04
Ln(Population)	0.50	0.12	0.12	0.03
Percent white	0.33	0.06	0.18	0.05
Poverty rate	0.16	0.00	0.26	0.22
Multivariate L1	0.97	0.79	0.97	0.71
Number of Observations: Treated, Control	156. 437	34, 31	386, 207	62, 55

Appendix 2.B. Logit Models for Treatment 1 and Treatment 2 for Non-Metropolitan and Metropolitan Counties

	Non-Metropolitan Counties		Metropolitan Counties	
	Treatment 1: OTP in County before 2013	Treatment 2: OTP in Neighboring County before 2013	Treatment 1: OTP in County before 2013	Treatment 2: OTP in Neighboring County before 2013
Age Adjusted Death Rates (2011-2013)	-0.01	0.04**	0.05***	0.03
Prescription rate	0.01	6.3e-3*	0.01**	-0.01***
Ln(Population)	1.02	1.59***	1.91***	-0.02
Percent white	0.02	4.49e-3	-0.03**	1.78e-3
Poverty rate	9.51e-3	0.04	0.04	-0.10***
Constant	-15.43*	-18.07***	-23.51***	3.21
Number of Observations	157	157	331	331
R^2	0.06	0.07	0.34	0.08

*Note: ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively*

Appendix 2.C. Descriptive Statistics between Counties with Suppressed and Non-Suppressed Death Counts

	Age Adjusted Death Rates (2014-2016)						Age Adjusted Death Rates (2011-2013)					
	Non-Metropolitan Counties			Metropolitan Counties			Non-Metropolitan Counties			Metropolitan Counties		
	No Suppressed Counts	Suppressed Counts	Ttest	No Suppressed Counts	Suppressed Counts	Ttest	No Suppressed Counts	Suppressed Counts	Ttest	No Suppressed Counts	Suppressed Counts	Ttest
Covariates												
Prescription rate	145.70	86.16	***	105.29	75.55	***	144.47	88.74	***	104.93	80.44	***
Population	41,897.95	18,742.72	***	240,007.10	33,268.09	***	41,511.58	19,727.41	***	256,917.80	42,677.87	***
Percent white	81.08	66.62	***	70.30	70.33		81.08	66.62	***	70.30	70.33	
Poverty rate	21.08	21.86		15.55	17.90	***	20.93	21.87	*	15.53	17.58	***
Number of Counties	183	647		370	223		157	673		331	262	

*Note: *** and * represent statistical significance at the 1% and 10% level, respectively*

Appendix 4.A. Flyer Used to Advertise Community Meetings

Ardmore Community Meetings

on Approaches for the Opioid Crisis

This series of 3 meetings will focus on community options for responding to the opioid crisis. Come share your experiences dealing with the epidemic and learn from others who are working in this area.

FEATURING A SPECIAL SHOWING OF "KILLING PAIN"

WHEN *Please attend all 3

-February 6th (Wed)
-February 20th (Wed)
-March 5th (Tues)
2 – 4pm

WHERE

Mercy Hospital Conference Center

1011 14th Avenue NW
Ardmore, Oklahoma

Please RSVP: https://ardmoremeetings.rsvpify.com

SPEAKERS

Ardmore Police Department

Break Thru Withdrawal Network

Dr. Layne Subera

Oklahoma Bureau of Narcotics and Dangerous Drugs

Wichita Mountains Prevention Network

QUESTIONS?

Contact Devon Meadowcroft
devon.meadowcroft@okstate.edu
Phone: 405-744-9880

OKLAHOMA STATE UNIVERSITY EXTENSION

Participation in these meetings can assist in your organization receiving future grant funding

Appendix 4.B. List of Represented Organizations at Community Meetings

Organization
Arbuckle Life Solutions
Ardmore Behavioral Health Collaborative
Ardmore Police Department
BreakThru Medical Withdrawal Services at Mercy Hospital
Carter County - OSU Extension
Carter County Health Department
Carter County Sheriff's Office
Chickasaw Nation
Destiny Recovery Center
Family Shelter of Southern Oklahoma
Good Shepherd Community Clinic
INCA Community Services
Lighthouse Behavioral Wellness Center
Mercy Hospital
Oasis Staffing
Oklahoma Bureau of Narcotics and Dangerous Drugs
Oklahoma Department of Human Services
Oklahoma Department of Mental Health and Substance Abuse
Oklahoma Families First
Southern Oklahoma Treatment Services
Southern Tech
Take Two Academy
The Community Children's Shelter and Family Services Center
The Salvation Army
USDA Rural Development Division
Wichita Mountain Prevention Network

Appendix 4.C. Detailed Agenda for Community Meetings

Ardmore, Oklahoma Community Meetings on
Community Perceptions to Different Approaches for Solving the Rural Opioid Crisis

Location, Dates, and Time:

Location

- Mercy Hospital in Ardmore

Dates

- 1. February 6 (Wed)
- 2. February 20 (Wed)
- 3. March 5 (Tues)

Time

- 2 – 4pm

===

Meeting 1 Agenda (February 6)

2:00-2:15

- Introductory presentation
    - Opioid epidemic in Ardmore
    - Community meeting structure overview

2:15-2:20

- Introductory survey
    - Perceptions / knowledge level about programs
    - Basic demographic information

2:20-2:40

- Discussion of 4 categories of programs; examples from participants

2:40-3:10

- Documentary showing "Killing Pain" parts 1-3

3:10-3:30

- Presenter #1
    - Category A: Supply-side programs (Law enforcement, prescribing guidelines,…)
        - Oklahoma Bureau of Narcotics and Dangerous Drugs – Agent Craig Williams

3:30-3:50

- Presenter #2
    - Category B: Demand-side programs (Youth intervention, public health campaigns,…)
        - Wichita Mountains Prevention Network – Lisa Jackson & Jayci Enerson

3:50-4:00

- Meeting 1 debrief and preview of Meeting 2

===

Meeting 2 Agenda (February 20)

2:00-2:10

- Brief re-cap of Meeting 1 and introduction on what will be occurring in Meeting 2

2:10-2:40

- Documentary showing "Killing Pain" parts 4-6

2:40-3:00

- Presenter #3
    - Category C: Treatment programs (MAT, abstinence-based programs,…)
        - Dr. Layne Subera and Southern OK Treatment Services – Sasha Rogers

3:00-3:20

- Presenter #4
    - Category D: Overdose prevention / recovery (Naloxone provision)
        - Ardmore Police Department – Deputy Chief Kevin Norris
        - OK Dept of Mental Health & Substance Abuse – Mary Kate Cole

3:30-3:50

- Study circle #1
    - Participant views on *why* the opioid epidemic is occurring in the Ardmore community

3:50-4:00

- Debrief of Meeting 2 and preview of Meeting 3

===

Meeting 3 Agenda (March 5)

2:00-2:15

- Brief re-cap of Meetings 1 and 2 and introduction on what we will be occurring in Meeting 3

2:15-2:45

- Study circle #2
    - Participant thoughts on the programs presented, and the assets of the Ardmore community that make these programs feasible

2:45-3:15

- Group discussion / voting exercise
    - Each study circle reports findings, and each participant votes on which program they believe is the best fit for Ardmore

3:15-3:30

- Closing survey

3:30-3:45

- Community de-brief

Appendix 4.D. Select Pictures from Ardmore Community Meetings

Appendix 4.E. Pre/Post Survey

Please create a 4 digit ID for the survey. The first 2 digits should be the 1st and 3rd letters of your first name, with the second 2 digits being the day of the month that you were born (ex. If your name is John and you were born on December 5th, your ID would be JH05)

4 digit ID: ___ ___ ___ ___

What Should We Do about the Opioid Epidemic?

1. Do you agree or disagree with the statements below?	Strongly Agree	Somewhat Agree	Somewhat Disagree	Strongly Disagree	Not Sure
a. Like alcoholism, opioid addiction should be treated as a disease, not a crime.	○	○	○	○	○
b. The justice system should go after people who smuggle, deal, and sell opioids rather than spending time and resources on users.	○	○	○	○	○
c. We should continue to pass laws that limit the amount of opioid medications doctors can prescribe for patients who complain about pain.	○	○	○	○	○
d. People who are addicted to opioids that can't get or hold decent jobs should not be able to collect disability and welfare payments.	○	○	○	○	○
e. Providing medication to assist with overcoming addiction is more important than having a peer recovery support team in place.	○	○	○	○	○

2. Do you favor or oppose each of these actions?	Strongly Favor	Somewhat Favor	Somewhat Oppose	Strongly Oppose	Not Sure
a. Our top priority should be reducing access to opioids, EVEN IF it means we invest less money and effort in treatment.	○	○	○	○	○
b. Sentencing for dealing and distributing opioids should be sharply increased, EVEN IF it means straining our prison capacity.	○	○	○	○	○
c. All opioid treatment centers should be covered by federal / other health insurance, EVEN IF this will increase taxes for everyone.	○	○	○	○	○
d. We should make naloxone, an overdose treatment drug, widely available without prescription, EVEN IF it might encourage people to experiment with more dangerous drugs.	○	○	○	○	○

All information collected here is part of an OSU research project and is completely voluntary. If you have questions about this survey, please contact either Brian Whitacre at (405) 744-9825 or the OSU IRB staff at (405) 744-3377.

The goal of this workshop is to find out what the community of Ardmore thinks is the best way forward in addressing the opioid epidemic. We will focus on 4 different categories of programs:

- [A] Programs that try to reduce the supply of opioids
  - Examples: Law enforcement efforts, prescribing guidelines for physicians, legislation on doctor shopping, prescription drug monitoring programs, prescription take-back programs
- [B] Programs that try to reduce the demand for opioids
  - Examples: Public health campaigns, youth intervention programs, reduced marketing of opioids
- [C] Opioid treatment programs
  - Examples: Medication assisted treatment (MAT), abstinence-based programs, peer recovery support
- [D] Naloxone (an overdose treatment drug) access and training
  - Examples: Naloxone access / education, treatment options after overdose reversal

Please indicate your level of familiarity with these programs in your community:

Category	*Not familiar at all*	*Slightly familiar*	*Moderately familiar*	*Very familiar*	*Extremely familiar*
Programs that try to reduce the supply of opioids					
Programs that try to reduce the **demand for opioids**					
Opioid treatment programs					
Naloxone access and training					

For each category, select how effective you think these efforts currently are in addressing the epidemic, and if you believe more or less resources should be devoted to these programs in your community.

[Category A]: Prevention Options (*Supply-side focused*)

1. How effective do you think these efforts ***currently*** are in addressing the opioid epidemic in Ardmore?

○ Very ineffective ○ Somewhat ineffective ○ Neither ○ Somewhat effective ○ Very effective ○ I do not know

2. In your opinion, should the Ardmore community devote ***more*** **or** ***less*** resources to efforts in this area?

○ Significantly less ○ Somewhat less ○ Neither ○ Somewhat more ○ Significantly more ○ I do not know

[Category B]: Prevention Options (*Demand-side focused*)

1. How effective do you think these efforts ***currently*** are in addressing the opioid epidemic in Ardmore?

○ Very ineffective ○ Somewhat ineffective ○ Neither ○ Somewhat effective ○ Very effective ○ I do not know

2. In your opinion, should the Ardmore community devote ***more*** **or** ***less*** resources to efforts in this area?

○ Significantly less ○ Somewhat less ○ Neither ○ Somewhat more ○ Significantly more ○ I do not know

[Category C]: Opioid Treatment Programs

1. How effective do you think these efforts *currently* are in addressing the opioid epidemic in Ardmore?

○ Very ineffective ○ Somewhat ineffective ○ Neither ○ Somewhat effective ○ Very effective ○ I do not know

2. In your opinion, should the Ardmore community devote ***more*** **<u>or</u>** ***less*** resources to efforts in this area?

○ Significantly less ○ Somewhat less ○ Neither ○ Somewhat more ○ Significantly more ○ I do not know

[Category D]: Naloxone Access and Training

1. How effective do you think these efforts *currently* are in addressing the opioid epidemic in Ardmore?

○ Very ineffective ○ Somewhat ineffective ○ Neither ○ Somewhat effective ○ Very effective ○ I do not know

2. In your opinion, should the Ardmore community devote ***more*** **<u>or</u>** ***less*** resources to efforts in this area?

○ Significantly less ○ Somewhat less ○ Neither ○ Somewhat more ○ Significantly more ○ I do not know

---

Please indicate the percentage of total efforts you think the community *currently* puts into each option

____ [Category A]: Supply-side prevention
____ [Category B]: Demand-side prevention
____ [Category C]: Treatment options
____ [Category D]: Overdose prevention / recovery

Please indicate the percentage of total efforts you think the community *should* put into each option

____ [Category A]: Supply-side prevention
____ [Category B]: Demand-side prevention
____ [Category C]: Treatment options
____ [Category D]: Overdose prevention / recovery

For each question, the 4 values should add up to 100% (ex. 30% to supply-side prevention, 20% to demand-side prevention, 30% to treatment options, and 20% to overdose prevention / recovery → should sum to 100%)

What is your ethnicity?

- ○ African American
- ○ Caucasian/White
- ○ Hispanic/Latino
- ○ American Indian
- ○ Asian
- ○ Other

What is your annual household income?

- ○ Under $25,000
- ○ $25,000 - $49,999
- ○ $50,000 - $74,999
- ○ $75,000 – $124,999
- ○ $125,000 or more
- ○ Prefer Not to Answer

What is the highest level of education you have achieved?

- ○ Did not graduate high school
- ○ High school, GED, or Equivalent
- ○ Some College / Associates Degree
- ○ College Degree
- ○ Post College Degree

What is your political affiliation?

- ○ Republican Party
- ○ Democratic Party
- ○ Independent
- ○ Prefer Not to Answer

How do you receive your news?
(Rank from 1-5 with 1 being the most important and 5 being the least important)

____ Newspapers
____ Internet
____ Radio
____ Television
____ Social Media

What is your gender? ___ Male ___ Female

What year were you born? ________

How many years have you lived in the Ardmore area? _____

Please provide your opinion on what will be required to successfully address the opioid epidemic in Ardmore:

____

____

Appendix 4.F. Study Circle Questions

Study Circle #1 (Meeting 2, February 20)

Purpose: Participant views on *why* the opioid epidemic is occurring in the Ardmore community

Why is there Opioid Misuse in Ardmore?

Questions

1. Think about the Ardmore community. As a group, discuss the underlying reasons for why opioid misuse is an issue for this area. Use the space below to write down your reasons. Make sure to draw on the experiences / knowledge of everyone in the group.

2. As a group, come to a consensus on which of the reasons you listed are the most important (top 3).

3. Are there direct ties between any of the programs we have heard about so far and the reasons your groups have come up with? Discuss.

4. Which of the reasons for the opioid crisis that you discussed in Question 1 will be the easiest to address in the future? Which reason will be the hardest to address?

Reasons for Opioid Misuse in Ardmore

Study Circle #2 (Meeting 3, March 5)

Purpose: Participant thoughts on the programs presented, and the assets of the Ardmore community that make these programs feasible in the future

What Programs Should Ardmore Utilize in the Future?

Below is a table showing the 4 categories of programs that were presented on. In the right-hand column, list some assets that the Ardmore community has that are either currently responsible for these programs or could be helpful to their efforts.

Program Category	**Ardmore Assets**
[A]: Prevention options (Supply-side focused)	
[B]: Prevention options (Demand-side focused)	
[C]: Opioid treatment programs	
[D]: Overdose prevention and recovery	

<u>Questions</u>

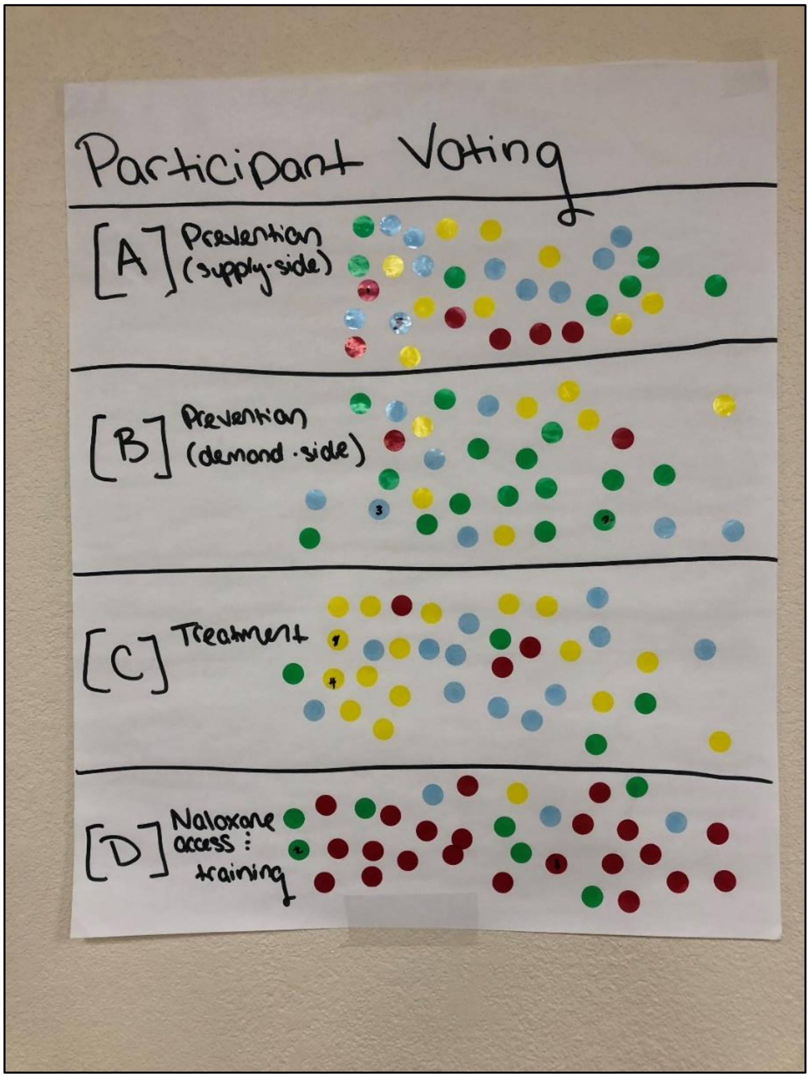
1. Think back to the reasons for the opioid epidemic in Ardmore that we discussed in the last meeting. Do these four programs address the reasons for the opioid epidemic in Ardmore? Why or why not?

2. What programs from the presentations do you think should be expanded, and why? Which ones are you now less likely to support, and why?

3. What are the barriers to expanding or improving these programs? How might the community overcome these barriers?

4. Are there other efforts (outside of these four programs) that should be part of the discussion? What are they?

Appendix 4.G. Picture of Participant Voting Exercise Results



VITA

Devon P. Meadowcroft

Candidate for the Degree of

Doctor of Philosophy

Thesis: ESSAYS ON THE RURAL OPIOID CRISIS

Major Field: Agricultural Economics

Biographical:

Education:

Completed the requirements for the Doctor of Philosophy in Agricultural Economics at Oklahoma State University, Stillwater, Oklahoma in May, 2019.

Completed the requirements for the Master of Science in Agricultural and Resource Economics at University of Delaware, Newark, Delaware in 2016.

Completed the requirements for the Bachelor of Science in Animal Science at University of Vermont, Burlington, Vermont in 2013.

Experience:

Graduate Research Assistant at Oklahoma State University, August 2016 to May 2019.

Graduate Research Assistant at University of Delaware, August 2014 to May 2016.

Professional Memberships:

Agricultural and Applied Economics Association.